Network Centrality and Delegated Investment Performance[†]

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Abstract

We document a positive relation between network centrality and risk-adjusted performance in a delegated investment management setting. More connected managers take more portfolio risk and receive higher investor flows, consistent with these managers improving their ability to exploit investment opportunities through their network connections. Greater network connections are shown to be particularly important in reducing the diseconomies-of-scale for large managers who are well-connected. We also use the exogenous merger of two investment consultants, which creates a sudden change in the network connections of the managers they oversee, to provide evidence that a greater number of connections translates into better portfolio performance.

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1 Introduction

Modern delegated portfolio management, in the pension, foundation, and endowment sectors, involves a complex network of investment managers who each oversee a portion of the investment portfolio of a sponsor.[1] Such a network brings the potential for interactions between its members, including competitive pressures that motivate managers within a given sponsor portfolio. Investment consultants, with the power to recommend the hiring or firing of managers, have an incentive to monitor and discipline the managers they employ. Given that these consultants oversee numerous managers who provide investment management services for several funds, it is natural to expect that they would attempt to motivate their managers to gather information from their counterparts.[2]

While prior research has studied the influence of social networks on investment manager performance (e.g., Cohen, Frazzini, and Malloy, 2008; Coval and Moskowitz, 2001; and Christoffersen and Sarkissian, 2009), all of these papers measure network connections in an indirect way.[3] This is not surprising, as direct connections between fund managers (and between managers and corporate CEOs) are generally informal and undocumented. And, while investment consultants may keep records on the network of managers that they use at various funds, they are typically bound by their clients (the fund sponsors) to keep such data confidential. Indeed, in the US, there is no publicly available database–even for a fee–that identifies exact linkages between managers and sponsors, as well as the identity of the overseeing consultant.[4]

In this paper, we bring much more direct evidence to the question of the importance of manager networks in asset management. Specifically, our paper exploits a unique database that contains

[1]Delegated asset management, in the U.S., is a sector with over $8 trillion in assets (worldwide, large pools, such as sovereign wealth funds, add considerably to this figure). Specifically, the combined assets of U.S. defined-benefit pensions are estimated to be $7.86 trillion, as of Q1 2013 (http://www.pionline.com/article/20130626/ONLINE/130629908/ici-us-retirement-assets-hit-record-208-trillion). The largest 40 foundations and endowments, as of Q1 2014, held almost $500 billion in assets (https://www.graypools.com/report/2014/Q1/40-largest-foundations-endowments.html).

[2]A recent report from the UK's financial market regulator, the Financial Conduct Authority (FCA) writes "The importance of investment consultants as a gateway to the market can be seen by the large proportion of asset managers' institutional marketing budget which is spent on building relationships with investment consultants. This includes spending on things like sponsored events and conferences" (Financial Conduct Authority, 2016; Para. 8.70, p. 152).

[3]For example, Cohen, Frazzini, and Malloy (2008) measure connectedness through records that indicate that a fund manager and a corporate executive attended the same university. Coval and Moskowitz (2001) measure connectedness through the geographical distance between a manager and a firm. Christoffersen and Sarkissian (2009) measure connectedness using large cities as a proxy.

[4]For instance, Jenkinson, et al (2016) use survey data to infer how many sponsor clients are served by a particular manager, since exact relationship data are not available.

detailed data, both in a large cross-section and in a long time-series, on the connectedness between defined-benefit pension fund managers – one of the largest groups of delegated portfolio managers. Our dataset, which covers UK funds, is provided by a one-time granting of proprietary data to allow academic studies, and offers an unprecedented inside look into the precise network relationships between investment managers. Our dataset is unique in that it allows us to compute network connections in a very detailed manner. That is, for each calendar quarter in our sample from 1984-2004, we have information on the coded identity of each manager employed by each defined-benefit pension fund, the identity of the overseeing consultant, the return of that manager at that fund, and the sector in which that manager is expected to invest.[5] We use these data to provide evidence on how the network position of fund managers relates to their investment performance.[6]

Network connections in our dataset arise from two separate sources. First, in the defined-benefit pension fund sector, each fund manager oversees only a portion of an overall investment portfolio, with potentially many other managers overseeing the remainder even within a single asset class (e.g., equities). Such overlaps, in turn, create a network of connections across pension fund sponsor/manager ("fund-manager") pairings. For example, Manager 1 might manage a portion of the accounts of each of dozens of pension fund clients, many of whom have also hired Manager 2. This creates a manager-to-manager connection between managers 1 and 2 (we envision this connection as being facilitated by the single consultant to each pension fund sponsor).[7] As a second source of network connections, pension funds hire consultants to provide advice on which managers to hire, thus creating a network between, say, managers 3 and 4, through having a common consultant in their interactions with several fund sponsors even if the managers do not manage assets for the same pension fund at the same time.

Our unique database allows several new findings. Most importantly, we find that managers that are better connected (or more central in a network) tend to have higher risk-adjusted returns. We note that our regressions allow for fund-manager and time fixed-effects. The presence of a fund-manager

[5]In this paper, we refer to the overall sponsor portfolio as a "pension fund" or simply, "fund," and the particular fund within the sponsor portfolio that is overseen by a single manager as a "fund-manager."Finally, we refer to fund management companies as managers.

[6]Our dataset is also employed by Blake et al. (2013), who investigate the effect of the recent decentralization of pension fund management on investment performance. Here, we focus on the network connections between fund sponsors, fund managers, and investment consultants. There is a relation between the two papers: as decentralization has increased, network connections have multiplied. Thus, networks have become more complex and, hence, richer in cross-sectional variation, which allows us to conduct more powerful tests of the role of connectivity.

[7]In the pension fund industry, a single pension fund (sponsor) generally retains only one consultant.

fixed-effect controls for any ability of consultants to identify "good matches" between funds and managers – ensuring that we are not merely capturing that consultants tend to more frequently hire skilled managers (thus, making them more networked). Instead, the estimated effect of network centrality comes from time-series variation in the relation between network centrality and risk-adjusted performance of a given manager at a given fund.[8] The positive relation between risk-adjusted performance and centrality is also robust to the inclusion of consultant fixed effects – which further ensures that our findings are not driven by the ability of a subset of consultants to identify (future) successful fund-manager matchups. When we decompose the network into manager-to-manager and consultant-to-manager connections, we find that both types of connections appear to be important, with the latter having a somewhat larger effect. Moreover, our results are not explained simply by more central managers being bigger, and, thus, more highly connected. In fact, while there is a positive correlation between manager size and centrality, size is negatively related to risk-adjusted performance in our sample (consistent with Chen, Hong, Huang, and Kubik, 2004), while centrality is positively related to risk-adjusted performance. We also find an interaction effect between fund-manager size and network centrality, which suggests that large funds use their domestic (UK) network centrality to counteract the negative effect of size on investment performance (i.e., diseconomies-of-scale).[9]

Second, we find that network connections have a large and significantly positive effect on fund flows – driven entirely by a manager attracting new pension fund assets rather than attracting more assets from existing clients – again, after controlling for size. In contrast, fund size has a negative effect on fund flows, whereas past returns have no effect on flows. This suggests that, controlling for size and past returns, the more central a manager is, the greater are the expected new-client inflows, consistent with pension fund sponsors (with the assistance of their consultants) understanding and endogenizing the value of a manager having a higher network centrality. It may also indicate that sponsors (and their consultants) use a manager's centrality in the network to form expectations about that manager's future performance, as opposed to only relying on (noisy) past performance.

[8]Predicting such time variation in skills by a given manager within a given fund is significantly more challenging for a consultant than simply predicting good performance "on average."

[9]Notably, we find little evidence that centrality within our network of UK managers affects the risk-adjusted returns for international equity managers, consistent with more "localized" benefits associated with network centrality. That is, the international managers appear to cover very different non-UK markets, making the information associated with each manager's investment strategy of more limited value to other managers.

Third, we find that managers with high centrality take more risk, consistent with more central managers having higher levels of private information deriving from their network position, and pension fund sponsors (and their consultants) tolerating this higher risk-taking because of superior average performance. To explore possible reasons for this finding, we explore whether network centrality influences the behavior of managers through the probability that they are fired by their pension fund clients. We find strong evidence that better connected managers face a significantly reduced probability of being fired, after controlling for size and past return performance. This finding is consistent with pension plan sponsors (and their consultants) understanding that more central managers have an information advantage over less well connected managers.[10]

To summarize, our results suggest one significant reason why some pension fund managers are successful, while others are not. Being centrally located in a manager network fosters better risk-adjusted investment performance, higher inflows, and an ability to reduce both the negative impact of size that affects most funds as they grow large and the risk of being fired. While we believe that an "information transmission" mechanism is a plausible explanation for the positive association between network centrality and future risk-adjusted performance, we do not directly observe information flows, and an alternative mechanism may also be at work. Specifically, investment consultants may choose particular fund managers because they like that manager's investment style and believe it fits well with a particular sponsor's overall set of managers. In this case, no information is transmitted from a manager to another from their connections via a common consultant, but the consultant's network connections allow him to better identify fund managers having styles that load on (potentially time-varying) priced risks that may not be captured by our risk model. Because we do not directly observe the information flow between fund managers, we cannot rule out such a "priced-risk" mechanism. Nevertheless, we find strong evidence that our findings are not driven by a "reverse causality" mechanism, whereby skilled investment performance leads to a better network position for the manager.

Other papers in the finance literature have also found that networks can affect investment performance. Hochberg, Ljungqvist, and Lu (2007) examine the effect on venture capital (VC) firm performance of networks established through syndicated investments, and find that more central VC

[10]The control for size in this model eliminates the possibility that more networked managers are less likely to be fired simply because of the market power that might be possessed by large managers over consultants or their sponsors.

firms experience significantly better fund performance. Hochberg, Ljungqvist, and Lu (2010) find that incumbent VCs use their networks to restrict the entry of new (outside) VCs, thereby strengthening their bargaining power over entrepreneurs. Ozsoylev, Walden, Yavuz, and Bildik (2014) find that investors that are central in a network tend to trade earlier and earn higher returns than more peripheral investors. Pareek (2012) studies the implications of information networks on mutual fund trading behavior and stock returns, and finds evidence of information linkages between funds with large positions in the same stocks. Ahern (2013) investigates the relation between network centrality and the cross-section of stock returns and finds that stocks in industries that are central in networks of intersectoral trades, on average, earn higher returns than stocks in more peripheral industries. Buraschi and Porchia (2012) relate networks that connect firms' fundamentals to the cross-section of expected returns and find that central firms have higher expected stock returns.[11]

Our paper contributes to the literature on both networks and delegated portfolio management. Our data allow a deep analysis of how connections between professional investment managers–through providing management services for the same fund or through the same investment consultant–contributes to their success in generating portfolio performance. We show that networks between portfolio managers are a heretofore unexplored and important factor in the delegated portfolio management sector.

Our paper proceeds as follows. Section 2 introduces our data and presents empirical evidence on the networks. Section 3 explores the relation between risk-adjusted return performance and network centrality, while Section 4 discusses possible interpretations of our findings. Section 5 considers the dynamic relation between fund flows and network centrality by estimating models that relate fund flows to past flows, size, return performance, and network centrality. Section 6 considers how funds' risk-taking behavior is linked to their network centrality and analyzes if centrality affects managers' incentives through their risk of being fired. Section 7 concludes. Additional results are contained in appendices at the end of the paper.

[11] A number of studies present empirical evidence that social networks play an important role in explaining investors' trading decisions and portfolio returns; see, e.g., Hong, Kubik and Stein (2004), Ivkovic and Weisbenner (2007) and Cohen, Frazzini and Malloy (2008, 2010). Stein (2008) develops a model of incentive-compatible information exchange between competitors bouncing ideas off each other and motivates his theory of word-of-mouth conversations through professional money manager networks. Equilibrium effects of financial networks are analyzed by Colla and Mele (2010), Ozsoylev and Walden (2011) and Walden (2015).

2 Data and networks

This section describes the data on UK pension funds used in our study, and explains the networks established between funds, managers, and consultants for the most important asset class held by these funds, UK equities. Next, we describe how we construct the centrality measures used in our analysis and provide insights into their characteristics, evolution over time, and correlations with other variables in our dataset.

2.1 Data

Our unique dataset comprises quarterly returns and asset holdings of 2,385 occupational defined benefit pension plans between March 1984 and March 2004. The data, which were generously provided by BNY Mellon Asset Servicing, contain information on seven asset classes, but we concentrate on the biggest one – UK equities – which, on average, comprises about 50% of asset holdings, by market value, during our sample.[12] For each fund, we know the coded identity of the fund manager – or managers in cases with multiple managers – at each point in time. This is important, since it is common, especially for large funds, to employ two or more specialized managers, e.g., a large and a small cap equity manager.

Such overlaps create the potential for network effects, as fund sponsors (on the advice of their consultants) coordinate the investment decisions across different managers so as to minimize the inefficiency loss associated with decentralized decision making (e.g., Sharpe (1981), van Binsbergen et al. (2008), and Blake et al. (2013)). Funds may also indirectly reveal information about other managers' investment strategies by setting up competitions among managers, ensuring that the best-performing managers see their assets under management increased at the expense of worse-performing competitors.

[12]UK equities comprise 50.7%, 57.9%, and 42.7% of asset holdings in 1984, 1994, and 2004, respectively. The other asset classes are cash, UK bonds, international equities, international bonds, index-linked bonds, and property.

2.1.1 Managers

Table 1 shows the number of fund-manager pairings – the unit of observation for much of our analysis – at three points in time (1984, 1994, and 2004).[13] The number of fund-manager pairings starts at 1,204, increases to 1,420, then declines to 1,053 by the end of the sample.[14] Table 1 also reports the number of funds in the dataset at the same three points in our sample. Between 1984 and 1994, the number of UK equity funds increased slightly. The number of funds then decreased between 1994 and 2004. Comparing the number of fund-manager pairings to the number of funds, it is evident that, over our 20-year sample, a large number of funds moved from being single-managed to being multi-managed – a change in paradigm analyzed in detail by Blake et al. (2013). For example, the average number of UK equity managers per fund went from 1.26 in 1984 to 1.67 in 2004.

The remaining columns of Table 1 present the number of managers as well as summary statistics for the number of connections per manager. The number of UK equity managers in our sample declined from 113 in 1984 to 82 in 2004. At the same time, the number of network connections per manager increased over time, indicating that the pension fund management industry became more concentrated among fewer managers who, in turn, became more inter-connected over time. For example, the proportion of managers with more than 20 network connections increased from 7% in 1984 to 12% of the managers in 2004.

2.1.2 Consultants

The pension funds in our sample are advised by consultants who play a very significant role in the appointment of fund managers and the choice of investment mandates, as well as monitoring managers after they are hired.[15] A total of 12 different consultants performed these services at some point during our sample period. During our sample, the market for consultants was dominated by four large firms whose combined market size did not change much. Notably, two consultants – one catering to many small funds, the other to large funds – merged in 1998. This merger, which we will examine later,

[13] Each time a manager is given a portion of a pension fund's assets to manage, a separate account is set up whose assets and return performance are tracked through time.

[14] This decrease is the result of sponsors switching from defined-benefit to defined-contribution pension plans.

[15] As of June 2011, $25 trillion of institutional assets worldwide were advised by investment consultants, and in certain countries, like the UK, defined-benefit pension fund sponsors are required by law to seek the advice of investment consultants in their investment decisions.

increased the scope of advisory services (i.e., both large fund and small fund consulting services under one umbrella) for the merged consultant entity, with little overlap.

2.2 Network relations

A network is characterized by its nodes (agents) and edges (connections). To construct networks, we include all agents (funds, fund managers and consultants) present at a given point in time. This allows us to construct a time series of network connections.

To illustrate how our network of funds, managers, and consultants are structured, Figure 1 shows a simple example comprising five pension funds, two consultants and five managers. Fund 1 is advised by Consultant 1 and employs Manager 1; Fund 2 is advised by Consultant 1 and employs managers 1 and 2; Fund 3 is advised by Consultant 1 and employs managers 2 and 4; Fund 4 is advised by Consultant 2 and employs managers 2, 3, and 4; finally, Fund 5 is advised by Consultant 2 and employs managers 4 and 5.

The top panel in the figure displays the full set of connections between pension funds, managers, and consultants–the so-called extended-form representation of the network. For each fund-manager connection, square boxes show the size of the associated account. Using this information, the bottom panel displays only the connections between managers and consultants–the so-called reduced-form representation–with green lines representing consultant-manager connections, and blue lines representing manager-manager connections arising when multiple managers co-manage the same fund. Managers 2 and 4 are seen to be particularly central in the network as they each manage accounts for three funds.

Having illustrated with the simple example in Figure 1 how the (reduced form) networks are formed, Figure 2 uses the full set of connections in our data set to form networks at three points in time during our sample, namely 1984, 1994, and 2004, for the UK equities asset class. Nodes shown as red circles represent individual managers, while the black diamonds in the horizontal row represent the 12 consultants.[16] Next to each node is the code of the manager or consultant. This code is specific to individual managers and consultants, and remains constant throughout the sample. Managers whose

[16]Note that some consultants may have very few (or even zero) connections in a given asset class and at a given point in time.

nodes are shown above the consultants are only connected to other managers through consultants (i.e., they did not co-manage a pension fund at that point in time), while managers whose nodes fall below the consultants are connected with at least one other manager though a contemporaneous presence in a pension fund. Blue lines in Figure 2 track network connections between managers (established through managers' sharing of the same pension fund client, and, thus, being linked through that fund's consultant) while green lines track connections between consultants and managers.[17]

2.3 Measuring network centrality

Network centrality can be measured in a variety of ways that are designed to capture different dimensions of the network. Because of such differences, and to ensure robustness of our empirical results, we consider three centrality measures, namely degree centrality, value-weighted prestige centrality and betweenness centrality. Degree centrality captures direct connections between nodes, but does not weight individual connections by their importance nor does it consider how well-connected these connections are, in turn. Value-weighted prestige centrality overcomes the first limitation of degree centrality by assigning different weights to direct connections, while betweenness accounts for the extent to which a node is a "hub" that serves to connect other nodes. We briefly introduce these three centrality measures in more detail.[18]

Our first measure of network centrality, degree centrality, measures the number of neighbors a node has, relative to the total number of nodes. For a specific network node–i.e., a manager or a consultant–this measure can be interpreted as the immediate probability that the node "catches" information flowing through the network. Formally, the degree centrality of node j at time t, DE_{jt}, is defined as:

$$DE_{jt} = \frac{d_{jt}}{N_t - 1}, \tag{1}$$

where d_{jt} is the number of connected neighbors for node j at time t and N_t is the total number of nodes in the network at time t.

[17] In 1994, 9 of the 12 consultants have multiple connections, while, in 2004, this number decreased to 7, showing the consolidation that took place in the consulting industry over the 20-year sample period. Some consultants have no connections to managers; they are shown, however, because they did have connections at a different point-in-time during our sample.

[18] See Billio et al. (2012) for a thorough discussion of the estimation of different network measures.

The second measure of centrality, value-weighted prestige centrality, is similar in spirit to degree centrality, but incorporates the idea that certain connections are more important than others. In our setting, the weight of each network connection is determined by the assets under management (AUM) that the manager manages through the recommendation of the consultant (summed across funds) or by the total sum of the assets under management when computing manager-to-manager network connections. Specifically, the value-weighted prestige centrality of node j at time t, P_{jt}, is defined as:

$$P_{jt} = \sum_{i \neq j} g_{jit} \frac{P_{it}}{d_{it}} \tag{2}$$

where g_{jit} is the (j, i) entry of the weighted connection matrix at time t; i, j refer to managers or consultants; and d_{it} is, again, the number of connected neighbors of node i at time t.[19]

Finally, betweenness centrality measures how many shortest paths connecting different nodes go through a particular node (manager or consultant). Hence it captures how important a node is in connecting other nodes. The betweenness of node j at time t, BE_{jt}, is thus defined as:

$$BE_{jt} = \frac{\sum_{k \neq i; j \neq k; j \neq i} \frac{P_j(k,i)}{P(k,i)}}{(N_t - 1)(N_t - 2)/2}, \tag{3}$$

where $P_j(k, i)$ is the number of shortest paths between k and i that pass through j, and $P(k, i)$ is the number of shortest paths between k and i.

As a concrete example of how the three centrality measures are computed, the table at the bottom of Figure 1 reports values for these measures using the data from the graphs in the figure. For example, a very small degree centrality of 2/6 is assigned to Manager 1, who is only connected to Manager 2 and Consultant 1 through Fund 1 and Fund 2. In contrast, Manager 2 is connected to managers 1, 3 and 4, and also to consultants 1 and and 2 (through funds 2, 3 and 4) and, therefore, has a very high degree centrality of 5/6. Turning to the value-weighted prestige centrality, we see that this can be quite different from degree centrality. For example, although managers 2 and 4 have identical degree centrality for our example, Manager 2 obtains a higher value-weighted prestige centrality than Manager 4 due to the slightly larger accounts handled by Manager 2. Finally, we see that some

[19] The definition reported in Equation (2) is self-referential. See Chapter 2 in Jackson (2008) for details on how to solve for P_{jt}.

managers that are peripheral in the network–notably managers 1, 3 and 5–get a betweenness measure of zero, meaning that no shortest path passes through these managers. In contrast, Manager 2 has the highest betweenness measure, because it is on the shortest path between other managers and consultants.[20]

Returning to our UK pension fund data, Figure 3 plots the distribution of centrality measures at three points in time. Note that the distribution of value-weighted prestige centrality is considerably more concentrated at small values than degree centrality, which is more spread out. The dispersion in betweenness centrality falls between the other two measures. These differences reflect that degree centrality is an unweighted measure of connectedness, unlike the other two. In addition to such differences across centrality measures, we also observe considerable variation over time for each centrality measure. As we shall see, such time variation in network centrality is informative in helping us to identify the effect of network centrality on performance.

2.4 Evolution of the networks

Figures 2 and 3 suggest that the number of network connections has changed substantially over time. To gain a better sense of how the "average" centrality measure has evolved during our sample, we next study the time-series of the average centrality measures. Each calendar quarter we first standardize every centrality measure by subtracting its time-series average and standard deviation over the full sample, so as to create a measure with mean zero and unit variance. Specifically, let $NET_t = M_t^{-1} \sum_{j=1}^{M_t} NET_{jt}$ be the cross-sectional average centrality measure at the beginning of quarter t, averaged across the M_t managers in existence, while $MEAN(NET_t)$ and $STDEV(NET_t)$ are time-series statistics of NET_t computed over the sample 1984-2004. The standardized centrality measure is then constructed as follows:

$$S\_NET_t = \frac{NET_t - MEAN(NET_t)}{STDEV(NET_t)}. \tag{4}$$

Figure 4 plots the time series of the normalized centrality measures, S_NET_t, over our sample

[20]Note that, even in this very simple case, the computation of betweenness centrality for a given node is quite complex as it requires considering the 21 total possible connections between each node in the network, i.e., Consultant 1 and Consultant 2, Consultant 1 and Manager 1, Consultant 1 and Manager 2, etc.

period. For all three centrality measures, we see a distinct upward trend between 1991 and 1998, interrupted by a merger-related drop in October 1998, a consolidation to 2002, and a large increase starting in 2003. Figure 4 indicates that the three centrality measures share a common trend component, but also that each measure of centrality captures somewhat different short-run information.

Panel B in Table 1 uses correlations to summarize the relation between our three network measures, as well as their correlation with fund-manager size and manager size. The three network measures are strongly, but not perfectly correlated, with average correlations around 0.90. In turn, the three centrality measures are virtually uncorrelated with fund-manager size, but have a positive correlation (0.61-0.66) with manager size (total management company UK equity AUM in our dataset). We would expect larger managers to have more network connections, but the results here suggest that manager size only accounts for a modest proportion of the variation in network centrality, raising the prospects that we can identify the separate effect of network centrality and size on a given manager's investment performance. We address this question in the next section.

3 Return performance and network centrality

This section addresses how the location of fund managers in a network influences their investment performance. We first explain how we construct a measure of the dependent variable (risk-adjusted returns), then present results from panel regressions that use centrality as a covariate, while controlling for fund-manager and time fixed effects, as well as fund and fund-manager size.

3.1 Risk-adjusted returns and network centrality

To explore the relation between risk-adjusted returns and network centrality, we first construct an estimate of risk-adjusted returns. Specifically, for each fund-manager pairing, we compute quarterly UK equity returns net of a three-month risk-free rate, r_{ijt}. Here, the subscript i refers to the fund, while j refers to the manager and t refers to the calendar quarter. We next regress this on the excess returns on the UK stock market index, $r_{mkt,t}$, returns on a UK size factor, SMB_t, a UK value-growth factor, HML_t and a UK momentum factor, MOM_t:[21]

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} r_{mkt,t} + \beta_{2ij} SMB_t + \beta_{3ij} HML_t + \beta_{4ij} MOM_t + \varepsilon_{ijt}. \tag{5}$$

Fund-manager pairings that survive for less than 12 quarterly observations are dropped as they would result in insufficiently precise estimates. Using the resulting estimates, for each fund-manager and each quarter, we compute the associated risk-adjusted returns, $\widehat{r}^{adj}_{ijt} = \widehat{\alpha}_{ij} + \widehat{\varepsilon}_{ijt}$.

Using our estimates of risk-adjusted performance from Equation (5) as the dependent variable, we perform panel regressions that include both fund-manager and time fixed-effects, that control for fund-manager and manager size, and that use standard errors that are clustered at the fund-manager level. To control for size effects on performance, we include terms that control for both fund-level and management company-level scale economies (or diseconomies). First, we compute the size for each fund-manager pairing, $SIZE_{ijt}$, measured as the market value of UK equity assets controlled by management company j for fund i at the beginning of quarter t. Second, for each management company, we compute the UK equity assets under management across all funds managed at the beginning of quarter t, labeled $M\_SIZE_{jt} = \sum_{i=1}^{Man_{jt}} SIZE_{ijt}$, by summing manager j's funds across all (UK equity) mandates, Man_{jt}. Each quarter, we convert these to relative size measures by taking the log of the size variable divided by its cross-sectional average, e.g., $\log(M\_SIZE_{jt}/M\_SIZE_t)$, where $M\_SIZE_t = M_t^{-1} \sum_{j=1}^{M_t} M\_SIZE_{jt}$ is the cross-sectional average manager size, averaged across the number of managers in existence at time t, M_t. This normalization helps to control for any time-varying industry-level diseconomies-of-scale, as documented by Pastor, Stambaugh, and Taylor (2015).[22]

Since we wish our panel regressions to test for the effect of network centrality on performance, unless otherwise noted, we normalize each of the network centrality measures for manager j by scaling it by the cross-sectional average, i.e., NET_{jt}/NET_t, thus accounting for time-series trends in the overall network structure which might otherwise affect our econometric estimates. Centrality is always

[21] We use the FTSE All-Share Total Return Index as the UK stock market portfolio, $r_{mkt,t}$. The factors SMB_t, HML_t, and MOM_t are UK versions of the factors commonly used for US equities. They are supplied by Professor Alan Gregory of Exeter University (http://xfi.exeter.ac.uk/researchandpublications/ portfoliosandfactors/index.php).

[22] We note that industry-level diseconomies, due to the significant size of the UK pension fund industry relative to UK equity markets, are captured separately through the quarterly time dummies.

measured ex-ante, i.e., prior to the return measurement quarter. It is also likely that any advantages conferred by a high level of network centrality are better exploited by larger management companies. To capture possible scale effects of network centrality, we add an interaction term between network centrality and manager size, $NET_{jt} \times M\_SIZE_{jt}$. To ease the comparison of estimated coefficients, we standardize all regressors so that they each have unit variance.

Table 2 presents results from panel regressions of the form

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} \times M\_SIZE_{jt} + \varepsilon_{ijt}. \quad (6)$$

This regression allows us to study the effect of network centrality, NET_{jt}, while controlling for variations in fund-manager size or management company size, and allowing for fund-manager and time fixed effects. Thus, we use variation *over time* in network centrality for a given fund-manager combination to identify its effect on risk-adjusted performance. We show results without and with the network-size interaction term $NET \times M\_SIZE$ in odd and even columns, respectively. Panel A uses degree centrality, Panel B uses value-weighted prestige centrality, and Panel C uses betweenness centrality.

First, consider the effect of size on risk-adjusted performance, across regression specifications, as shown in the first two rows of Table 2. Across all model specifications, fund-manager and total management company size negatively predict performance–consistent with past literature.[23] Moreover, the negative effect of manager size on performance is largest and always highly statistically significant. This suggests that any diseconomies of scale are determined by the size of the manager, rather than by the size of the account, which makes sense since a management company can be expected to employ similar strategies across its different fund accounts.

Turning to the relation between network centrality and performance, the estimates reported in row three show (for models without an interaction effect) that there is a strongly positive effect of centrality on risk-adjusted performance. The coefficient is economically and statistically significant – a

[23]Notably, Chen, Hong, Huang, and Kubik (2004), find negative economies at the fund level but positive economies at the management company level for the U.S. mutual fund industry. Our finding of diseconomies-of-scale at the management company level is likely due to the fact that pension fund management companies comprise a much larger fraction of the total market capitalization in the UK, relative to mutual funds in the U.S. Large management companies in the UK, therefore, face difficulties in trading their positions that outweigh other advantages of being large (such as being able to cross trades within the company or share a large pool of analysts).

one standard deviation increase in network centrality (controlling for size of mandate and management company) raises the expected risk-adjusted return by between 0.20% and 0.31% per annum. This finding holds across the three different centrality measures (Panels A-C), and irrespective of whether we include consultant fixed effects.

The direct effect of a one standard deviation increase in centrality (20-30 bps per annum, depending on the specification) may seem relatively modest. However, our estimate of the effect of centrality on fund performance is comparable to that found for many other fund characteristics by Ferreira et al (2013). Specifically, analyzing a large set of non-US funds,[24] Ferreira et al. (2013) find that a one standard deviation change in fund size, fund family size or fund age is associated with improvements in future performance of 44, 32, and 24 basis points per year, respectively.

Finally, in row four we find a strongly positive effect from including a centrality/management company size interaction term. The significance of the interaction term confirms that the performance of large managers is more sensitive to network centrality than that of small managers, which also implies that a central position in the network helps management companies cushion the otherwise strongly negative effect of their aggregated assets (under management) on performance. This interaction effect is so important that NET, by itself, now becomes insignificant – well-connected small management companies are less able to exploit their centrality.

3.1.1 Combined effect of manager size and centrality on performance

Table 2 reveals a significant but opposing impact on risk-adjusted returns coming from the size variables, M_SIZE and $SIZE$, and the centrality variables, NET. For example, the results in the second column of Panel A in Table 2 show that the coefficients on $SIZE$ and M_SIZE are negative (-0.292 and -0.722, respectively) while the coefficients on NET and $NET \times M\_SIZE$ are positive (0.042 and 0.365, respectively).

We illustrate the combined effect of size and centrality through a simple exercise that computes the combined (marginal) effect of the size and centrality variables on performance. We focus on large funds and managers as captured by the 75-th, 90-th, and 95-th percentiles of the size distributions.

[24] Ferreira et al. (2013) do not single out these results by country, so non-US funds is as close as we can get to UK funds.

For example, denote the 75-th percentile of $SIZE$ and M_SIZE as $SIZE\_75$ and M_SIZE_75. From Panel A in Table 2, the combined effect of size and centrality on fund performance is

$$\begin{aligned} Combined\_Effect = & -0.292\ SIZE\_75 - 0.722\ M\_SIZE\_75 + 0.042\ NET \\ & + 0.365\ NET \times M\_SIZE\_75, \end{aligned} \tag{7}$$

where we let NET range over its full support, i.e., from 0.07 to 4.08.

Figure 5 shows that, even for very large managers and funds (the 95-th percentiles of the size distributions), the joint effect of size and centrality is positive, as long as the centrality measure is greater than 2.5 (red line). This centrality value is relatively small, if we consider that large fund managers tend to have large centrality measures. In fact, 2.5 corresponds to the 75-th percentile for the NET degree centrality distribution in UK equities. Note also that, in all cases (all three lines), increasing centrality is associated with an increasing risk-adjusted return–illustrating that the "$Combined\_Effect$" always results in a positive first-order condition with respect to centrality.[25]

3.1.2 Decomposing the effect of network centrality

The network centrality measures used so far combine manager-to-manager and consultant-to-manager connections. In an effort to understand whether the superior performance of well-connected managers emerges from their manager-to-manager connections, their consultant-to-manager connections, or both, we focus on degree centrality and – for each manager and each time period – we construct separate centrality measures using either manager connections or consultant connections, but not both. We then re-estimate panel regression (6), including manager-to-manager (DEG_M) and consultant-to-manager (DEG_C) degree centrality. As expected, the two measures are closely correlated, but their correlation is low enough (0.82) that we can estimate their separate effects on investment performance. The results, reported in appendix Table A2, show that both types of centrality measures are related to investment performance. The coefficients are economically similar, but the consultant-to-manager centrality measure tends to have a slightly larger and more significant effect on investment perfor-

[25] To shed further light on the relation between fund-manager size and centrality, Appendix A conducts a panel Granger causality analysis. We find that centrality predicts future size whereas a manager's size fails to predict future centrality.

mance than the manager-to-manager centrality measure. Both types of network connections–through managers or through consultants–thus appear to be important in explaining the better investment performance of more central managers, with the latter type of network connection being slightly more important overall.

These findings are consistent with a mosaic theory of information acquisition, see Solomon and Soltes (2015). According to this view, consultants act as conduits for the diffusion of information while managers are able to collect information through their network connections and skillfully process this information in a way that leads to improved investment performance. Exploiting the information flowing through the network to improve investment performance may require combining such information with managers' other information sources and may also require managers' information processing skills. The central role played by consultants in the network therefore does not imply that consultants should be able to systematically pick successful managers – a point we discuss in Section 4.4.

4 Possible explanations for network effects

Section 3 established that network centrality matters for investment performance. We now explore potential mechanisms for this effect. First, to address whether managers gather information from their network, we decompose total fund returns into returns from systematic risk factors versus idiosyncratic returns, then analyze whether connected funds pursue more "similar" investment strategies than non-connected ones. Second, we shed further light on how network centrality may benefit investment performance by briefly considering its effect on performance in international equities.

This section also addresses the potential for "reverse causality" (performance leading to network centrality) in two ways. First, we use the merger between two consultants in our sample to perform a difference-in-difference analysis that explores how risk-adjusted performance changes after this exogenous shock to network centrality of some fund managers, relative to those not experiencing the shock. Second, because networks are endogenously formed, they could potentially be the result of a consultant's prediction of the future performance of a given manager at a given pension fund. If performance causes network centrality, we would expect that consultants should be able to identify the best performing fund managers. We, therefore, test whether consultants are systematically able to select successful managers.

Finally, we consider an alternative explanation for the impact of network centrality on performance, namely the possibility that network centrality matters to investment performance through managers' choice of investment style which could either attract or be influenced by the consultant.

4.1 Correlation between connected and non-connected managers

To further understand how network connections affect fund returns and performance, we next ask if we can detect similarities in investment strategies for managers that share one or more network connections. We measure performance using three different estimates of returns, namely, total, systematic (factor-induced), and abnormal (residual) returns (these return components are computed using Equation (5).) We proceed by, first, aggregating returns at the manager level by value-weighting returns across all funds managed by a given manager. We then compute return correlations for all possible pairings of managers in the dataset, subject to the manager pairings overlapping for at least 12 quarters, to obtain a reliable estimate of manager-to-manager correlations. Third, for each manager, we separately average the return correlations for that manager (i) with managers that are connected with that manager, and (ii) with managers that are not. Fourth, we compute the median of the average correlations across all connected and non-connected managers in the dataset. Fifth, and finally, we evaluate the differences in medians across the two sets of correlations using two-sided permutation tests with 1,000 iterations.

Table 3 reports the outcome of this analysis. The median correlations between total returns (first row) are very similar for connected managers, compared to non-connected managers. Specifically, the return correlation among connected managers is 95.4%, compared to 94.9% among non-connected managers and these correlations are not statistically different from each other. Of course, these high values may simply reflect the importance of common factors in explaining return performance, and not a tendency for certain managers to invest similarly. Therefore, we next explore, separately, systematic and idiosyncratic return correlations between managers.

Using the systematic return component, the second row shows that the median correlations computed across connected and non-connected managers are essentially identical. This result indicates that there is no difference in systematic risk-taking between connected and non-connected managers.

In sharp contrast, the third row reveals much greater differences in residual return correlations among connected and non-connected managers. Specifically, the median residual return correlation among connected managers is 17.0% versus 9.6% among non-connected managers. This difference in residual return correlations is statistically and economically significant. These findings are consistent with network positions affecting fund managers' security and sector selection strategies.

4.2 Network centrality and performance in international equities

Our main analysis focuses on the funds' UK equity holdings. However, as mentioned earlier, the pension funds in our sample hold investments in other asset classes, including international equities. UK pension funds are a much smaller fraction of the overall market in international markets than in domestic asset markets. As a consequence, a manager with a central position in the domestic equity market observes the preferred investment strategies of a large part of the market and should be better able to infer the resulting asset market equilibrium and possibly take advantage of this information, compared to the same manager in international stock markets.

To measure risk-adjusted performance, for international equities, we use a four-factor model that includes sterling-denominated excess returns on the MSCI North American (NA) and Europe Australasia Far Eastern ex-UK (EAFEX) Total Return Indices, as well as global size (SMB) and value-growth (HML) factors, all obtained from MSCI Barra:[26]

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} NA_t + \beta_{2ij} EAFEX_t + \beta_{3ij} SMB_t + \beta_{4ij} HML_t + \varepsilon_{ijt}. \tag{8}$$

For both the degree and betweenness centrality measures we find little evidence that network centrality affects investment performance in international equities, suggesting that the benefits from network centrality are limited to the domestic market in which the fund managers are major actors.[27]

[26] We include a North American market return factor separately due to the evidence in Timmermann and Blake (2005) that UK pension funds considerably overweighted this market in their international equity portfolio. We also experimented with versions of this model that add a momentum factor and found that this makes little difference to the results.

[27] Further supporting the evidence from this subsection, Appendix B provides results on the performance-centrality relation which control for centrality in other asset classes. We find that it is the network centrality within an asset class that matters to the performance-centrality relation.

4.3 The merger of two consultants: A natural experiment

The results presented so far indicate a positive relation between managers' network centrality and their ability to outperform. A potential concern with the results is that of reverse-causality: being well-connected can improve managers' risk-adjusted performance due to the resulting informational advantages, but an alternative explanation is that managers could be centrally placed in the network *because* they possess skills. Under this alternative mechanism, network centrality is the *result* of managers' skills, and not vice-versa.

To test the plausibility of this reverse-causality hypothesis, we use an exogenous shock in the network structure of the UK pension fund industry. On October 1, 1998, it was announced that two consultants (William M. Mercer and Sedgwick Noble Lowndes, consultants 2 and 11 in our data set) were merging. Mercer served mainly large clients, while Sedgwick Noble Lowndes served mainly small clients, so the merger was based on business synergies unrelated to any perceived future changes in the abilities of the two consultants to choose skilled managers.

Accordingly, this merger provides an exogenous shock to the centrality of those managers that were associated with the merged consultants. Before the merger, consultant no. 2 (Mercer) managed 202 mandates, while consultant no. 11 (Sedgwick) managed 213 mandates. After the merger, the number of joint mandates (two managers that manage assets at the same pension fund) jumped to 405. Some managers who, prior to the merger, were connected to either of the two affected consultants experienced an increase to their network centrality, while others saw it decline. We use the merger event to identify the effect of network centrality on investment performance.

Our analysis adopts a simple diff-in-diff approach that modifies the baseline specification in Equation (6) to include a treatment dummy interacted with the NET measure of centrality for all those managers connected to Consultant 2 (the surviving merged consultant) after 1998, the date of the merger. Specifically, we estimate for fund i, manager j, and time t:

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} \times M\_Dummy_{jt} + \varepsilon_{ijt}.$$

The merger treatment dummy M_Dummy_{jt} is switched on for three years after the merger for all managers involved in the merger. We choose a three-year window to allow the additional connections to have an impact on the managers' performance, but the results are robust – in fact, even stronger – when we use four- and five-year windows.[28]

The results, reported in Table 4, show that the interaction between the treatment dummy and centrality has a positive coefficient ranging from 0.074 for the betweenness measure to 0.153 for degree centrality. Moreover, for all three centrality measures the interaction term is statistically significant at the 10% level with the strongest result emerging for degree centrality, which generates a p-value of 0.02. These results indicate a significant and positive relation between being exogenously exposed to a shock to network centrality and subsequent risk-adjusted performance.[29]

4.4 Can investment consultants pick winners?

The above tests provide evidence that network centrality leads to superior performance, due to centrally located managers being better-positioned to receive information on the strategies of their competitors. As a final robustness check of this hypothesis vs. the reverse (managers are central because they are skilled), we test whether any of the consultants are systematically able to select successful fund managers. Consultants are the most well-informed entities in the UK pension fund industry, as they are able to closely observe the strategies of the majority of fund managers – which is why they are trusted in advising fund sponsors in their hiring and firing decisions. We conjecture that, if it is possible to identify successful managers in the industry, the consultants should be best-positioned to successfully perform this task. If consultants have the ability to predict which managers will outperform in the future, then they may place such superior managers in a larger network – even before they realize superior performance. Network centrality might, therefore, lead subsequent performance even though the direction of causality could be the reverse.

At the heart of this reverse causality mechanism lies the hypothesis that consultants can pick winners. To test this hypothesis, we estimate consultant fixed-effects in the regressions for risk-

[28] Our observations are fund-manager pairings, so these results are not due to managers perceived to be skilled being awarded more business by the merged consultant after the merger.

[29] As an additional robustness exercise, we also conducted a more refined analysis, which accounts for how individual managers' centrality was affected by the merger. We compute – for each manager – the change in the manager's centrality measures and assign the value 1 to the merger treatment dummy only for those managers that (i) are involved in the merger and (ii) whose (relative) centrality increases as a result of the merger. We find that the interaction between the treatment dummy and centrality has a positive and statistically significant coefficient close to 0.2 for two of the three centrality measures (degree and value-weighted prestige). For the third centrality measure (betweenness) the coefficient is positive, but small and insignificant.

adjusted performance. These fixed effects pool information across funds that are advised by the same consultant. Specifically, we adopt the specification,

$$r_{ict} = k + \alpha_c + \beta_{1ic} r_{mkt,t} + \beta_{2ic} SMB_t + \beta_{3ic} HML_t + \beta_{4ic} MOM_t + \epsilon_{ict}. \quad (9)$$

In this regression, i refers to the fund, c refers to the consultant, and t refers to the time period. Notice that we allow for consultant-fund differences by allowing the betas to differ across consultant-fund pairings.[30] This is an important consideration, since consultants often operate under different mandates for different funds. The estimated annualized alphas for the individual consultants are reported in Table 5. None of the consultants have alphas that are different from zero at the 95% confidence level (using a two-tailed t-test), suggesting that consultants are not systematically able to pick superior fund managers, a result consistent with the findings in Jenkinson et al. (2016).

To summarize, these results suggest that it is unlikely that managers are central in the network solely because they are skilled, and suggest that network centrality, in itself, offers certain advantages. Another consideration that renders reverse-causality less plausible is that regression (6) allows for fund-manager and time fixed-effects. The presence of a fund-manager fixed-effect means that we already account for the ability of consultants to identify "good matches" between funds and managers. Instead, the estimated effect of network centrality in (6) comes from time-series variation in the relation between network centrality and risk-adjusted performance.

4.5 Choice of investment style

We believe that the most plausible explanation for our findings is the following. First, a more central network position places a manager in an advantageous position to receive and process information. Specifically, such a central network position makes it easier for a manager to gather information and to observe his competitors' actions, including discovering which investment strategies work, and which do not.[31] We have shown evidence supportive of this view, including that managers tend to converge

[30] In these models, standard errors are clustered at the consultant-fund level.

[31] For instance, at the Q-Group (www.q-group.org), a large audience of well-networked fund managers interacts with a large number of fund sponsors. This interaction includes the presentation of investment strategies developed in-house (by a manager), as well as private face-to-face meetings between managers and sponsors. Managers that are more networked, i.e., work for more sponsors, are more likely to be invited to become members and to speak at such

toward each other's strategies (as measured by the correlation in their idiosyncratic risk), as well as evidence from a natural experiment showing that a merger between consultants changes individual managers' network centrality in a way that is positively correlated with investment performance.

However, for completeness, we note that we do not observe direct proxies for the flow of information in networks; we observe only the evolution of the structure of the network over time, and how it affects a given fund-manager relation. Accordingly, we note that an alternative explanation is that network centrality matters because of a manager's choice of investment style, which could either attract or be influenced by the consultant. For example, a manager may be selected by a consultant (perhaps acting on behalf of fund trustees), because the consultant likes the manager's investment style (say, a quantitative selection technique for equities). Alternatively, given its overview of the competitive landscape at a given point in time, a consultant may hire a manager and incentivize him to adopt the investment style of other managers – either by shifting loadings on existing risk factors or by loading onto new ones.[32]

While we cannot detect all shifts in exposure to omitted risk factors that might result from increased network centrality, we can explore whether there is evidence that variation in network centrality leads to time variation in funds' exposure to known risk factors. To do this, we, first, use a 12-quarter rolling window to estimate loadings on the market, SMB, HML, and MOM risk factors for manager j in fund i at time t. We then compute the quarterly time-series variation in the exposure of each fund-manager pairing to each risk factor as follows:

$$\Delta\beta_{Factor,ijt} = (\beta_{Factor,ijt} - \beta_{Factor,ijt-1}) \times 12. \tag{10}$$

Finally, we estimate – for each risk factor – the following panel regression:

$$\Delta\beta_{Factor,ijt} = a_{i,j} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \varepsilon_{ijt}, \tag{11}$$

professional conferences, since sponsors wish to know about, and to compare with, the strategies used by their colleagues.

[32] Investment consultants' ratings of fund managers provide another channel through which managers' choice of investment style may be correlated. Consultants' ratings are formed from a combination of quantitative (past performance) and qualitative (quality and stability of team, investment styles, philosophy, capacity for innovative ideas) measures. Through their monitoring efforts, investment consultant gain private information on each manager's strategy. These strategies across fund managers hired on the basis of the recommendations of the same consultant are likely to be correlated since the same measures score highly in the consultant-specific rating.

where $SIZE_{ijt}$ denotes the assets under management of each fund-manager pairing, M_SIZE_{jt} denotes the manager's assets under management in UK equities, cumulated across all funds managed, and NET_{jt} denotes the manager's network centrality. All variables have been transformed and standardized as previously described and all specifications use fund-manager and time fixed effects.

The results, reported in Table 6, suggest that, the more central a manager becomes, the more he focuses on small-capitalization stocks and value stocks. These are the types of stocks that are harder to value, and for which private information may be particularly advantageous. Conversely, managers focus less on momentum stocks as they become more central. This is true for degree centrality and betweenness centrality, whereas prestige centrality exhibits insignificance in this dimension. These findings are consistent with network centrality being related to managers' choice of investment style.

We also note that our original mechanism may be consistent with consultants as "gatekeepers," who randomly (or in exchange for some benefit) hire managers. In this mechanism, the managers who (somewhat by luck) are hired by a consultant see their network connections increase, and exploit this increased centrality to improve their strategies and performance. Consultants do not appear to be responsible for this, because many of their manager choices underperform (i.e., highly networked small fund managers). Thus, one must conduct the conditional regressions that we do in this paper, where we consider interactive effects of fund characteristics (i.e., size) and network centrality to detect the effect of centrality on manager skill-building.

Variants to these two mechanisms are also plausible. It is possible that a consultant hires a manager because the investment style of that manager fits well with other managers within a given pension fund, but that the manager improves her application of the style by learning from other managers with whom she has become networked and starts generating alpha from the strategy.

Finally, we must allow that there are other possible omitted variables that are correlated with network centrality. Among these could be scope efficiencies gained in trading when a manager serves many pension funds (cross-trading, for example); scope efficiencies gained by serving a larger pool of pension funds, each of which has their own idiosyncratic investment constraints and/or governance quality (e.g., trustees are either inattentive or very active and smart); and diversification in flow-related trading. We cannot rule out these alternative mechanisms in favor of the "information dissemination" mechanism, although our evidence seems more supportive of the latter.[33]

5 Fund flows and network centrality

We next address whether managers' centrality in the network affects flows of money into the funds they manage. We consider the results at the manager, rather than the fund-manager level, since defined-benefit flows for managers mainly occur through being hired (or fired) to manage additional (fewer) funds.

We split the analysis by considering inflows from existing mandates separately from inflows from new mandates. This distinction plays an important role for our sample of defined-benefit pension schemes. For existing mandates, high past returns may actually result in smaller inflows, as the sponsor rebalances toward a target allocation for the manager. This is a unique feature of our data that contrasts starkly with mutual funds, for which higher past performance tends to lead to stronger inflows. In our setting of defined-benefit pension plans, high network centrality is more likely to allow managers to grow assets through new clients, rather than existing ones.

For existing mandates, we generate our fund-flow variable for manager j over the course of quarter t as follows:

$$Flow_{jt+1} = \left(\frac{M\_SIZE_{jt+1} - M\_SIZE_{jt}}{M\_SIZE_{jt}} - R_{jt:t+1} \right) M\_SIZE_{jt}, \tag{12}$$

where M_SIZE_{jt} and M_SIZE_{jt+1} are the starting market values (of existing mandates) of manager j's asset holdings at quarter t and $t+1$ and $R_{jt:t+1}$ is the return generated over quarter t. For newly assigned mandates, the fund-flow variable for manager j over quarter t is the value of the newly assigned mandates.

Note that we analyze the level of flows rather than percentage flows (which are often used in studying flows to mutual funds). We believe that flow levels are more appropriate as the explained variable in our setting, as flows from sponsors are naturally capped by the dollar value of their aggregate (projected) liabilities. In addition, targets on asset allocation (which are commonly set by sponsors on the advice of consultants) means that an increased allocation of money to one manager comes

[33] For example, it is not clear, if more networked funds benefit from diversification in flow-related trading, why an increase in network centrality does not benefit smaller funds.

from a decreased allocation of the same amount of money from another manager. Moreover, fund size matters for a manager's ability to execute some types of investment strategies and this information is lost if we study percentage flows for small and large funds alike.

We regress the manager flow variable on lagged flow, network centrality, NET, and manager size, M_SIZE. We also include $Past\_Risk\_Adj\_Ret$, constructed by value-weighting the risk-adjusted returns across the various funds managed over the previous year. Finally, the regression includes time and manager fixed effects:

$$\begin{aligned} Flow_{jt+1} = a_j + c_t + \beta_1 NET_{jt} + \beta_2 Flow_{jt} + \beta_3 M\_SIZE_{jt} \\ + \beta_4 Past\_Risk\_Adj\_Ret_{jt} + \varepsilon_{jt+1}. \end{aligned} \tag{13}$$

The results for newly assigned mandates are reported in Panel A of Table 7. Our estimates show that network centrality is positively and significantly related to flows, and that this finding is robust with regard to which of the three centrality measures is used. As for the remaining coefficients, manager size is negatively and significantly related to flows, although its coefficient is only significant in the regression that uses degree centrality.[34] Past risk-adjusted performance is not a significant predictor of future flows while lagged flows are borderline significant at the 10% level with a positive coefficient. Thus, pension funds highly value networked managers when allocating their money–even more so than noisier measures of manager skill, such as past performance and lagged flows.

Turning to the flows for existing mandates (Panel B), the centrality coefficient NET is now insignificant for all three centrality measures, indicating that more central connected managers do not attract more flows from existing mandates because of their network position. This finding is consistent with our earlier observation that flows to existing accounts in defined-benefit pension plans cannot be expected to be very sensitive to forecasts of future performance. For existing mandates, we continue to find that past risk-adjusted performance is insignificantly related to flows, whereas the evidence that lagged flows predict future flows is stronger for mandates that are already in place.

Taken together, the results reported in this section show that network centrality does not seem to

[34]Note that this is strong evidence that sponsors (and their consultants) are keenly aware of diseconomies-of-scale in equities, as large funds generate lower flow levels than small funds. This evidence is much stronger than a finding of large funds gathering lower *percentage* flows.

explain managers' ability to attract greater flows among existing clients, but, notably, it is strongly related to managers' ability to acquire new clients. In light of the findings of Blake, et al. (2013) that sponsors tend to allocate only a portion of assets previously assigned to a poorly-performing manager to a new manager (and tend to be hesitant to fire the underperforming manager immediately), our results indicate that this new allocation tends to go to a manager with stronger network connections (and, thus, better expected future performance).

6 Risk-taking and network centrality

Section 3 established a positive association between fund-manager centrality and risk-adjusted investment performance. We next consider whether centrality affects managers' willingness to take risk, and the consequences of such actions. Network centrality could affect managers' risk-taking for at least two reasons. First, if more centrally placed managers have access to more precise information, they may be willing to take what appears to outsiders to be riskier bets. Second, if more centrally-placed managers are less likely to be fired for a given level of investment performance (as we find below), then they should also be willing to take riskier bets. We also note the importance of controlling for size in measuring risk-taking as larger managers will find it more difficult to deviate from the market benchmark due to the greater market impact of their trades and less maneuverability, compared with smaller managers.

6.1 Idiosyncratic risk and network centrality

We perform our analysis by proxying for the unobserved level of risk-taking by means of the level of idiosyncratic risk taken by a fund manager. Specifically, using Equation (5), we first extract an estimate of the fund-manager pairing's idiosyncratic risk, $|\widehat{\varepsilon}_{ijt}|$. Note that if these residuals are drawn from a Gaussian distribution, then $E[|\widehat{\varepsilon}_{ijt}|] = \sqrt{2/\pi} \cdot STDEV(\widehat{\varepsilon}_{ijt})$, thus justifying this particular proxy for risk. It should be recognized, however, that this is clearly a noisy measure of risk, as it is based on a single observation for every period.

Because of this limitation, we undertake the following procedure. From $|\widehat{\epsilon}_{ijt}|$, we subtract its cross-sectional average, computed using all the fund-manager pairings available at each point in time to control for time-varying volatility in markets. We then compute the time-series average of the demeaned absolute residuals at the fund-manager level, and use this as our measure of risk. Finally, we regress, at the fund-manager level, the average absolute residual on average centrality, fund-manager size, and manager size, all normalized using the procedures described earlier.

Results from this regression are presented in Table 8. First, notice that fund-manager size as well as manager size have a strongly negative effect on risk-taking across different specifications: larger fund-managers take on less active risk and mirror the benchmarks more closely. This makes sense, as it is more difficult for large managers to deviate from the market.

For all three centrality measures we find that funds with higher centrality take on more risk than less central funds. Moreover, the estimated slope coefficient on network centrality is highly statistically significant for two of the three measures (degree and value-weighted prestige). This finding is consistent with more central managers having higher levels of private information deriving from their network position and pension fund sponsors (and consultants) tolerating this higher risk level because of the associated higher level of expected performance.

6.2 Network centrality and hazards of being fired

Network centrality does not only affect the information flowing to and from a particular manager or consultant; it can also affect the manager or consultant's incentives. This can happen through its effect on flows of funds into and out of the funds under the manager's (consultant's) control and, thus, the manager's remuneration, which is likely to depend on the asset base; we analyzed this effect in Section 5. It can also happen through its effect on the probability that the manager is fired by a client. To investigate this second channel, we next analyze whether the probability that a manager is fired is affected by his network centrality.[35]

To assess whether a fund manager's or consultant's probability of being fired is influenced by his position (centrality) in the network, we estimate hazard rate models. The hazard rate (h) measures the probability of being fired next period, conditional on having survived up to the present time. To

[35] Previous studies have analyzed the factors influencing the likelihood of termination for mutual fund managers. Chevalier and Ellison (1999) report that young managers face a higher risk of being fired following poor risk-adjusted performance. Khorana (1996) finds that underperforming managers with decreasing inflows also face a higher probability of being fired. For VC firms Hochberg, Ljungqvist and Lu (2007) find that the portfolio companies of more central VCs are more likely to survive future financing rounds.

avoid having to impose restrictions on how the baseline hazard rate depends on the duration (d) of the relation between a manager and the pension fund, we use the Cox semi-parametric regression approach.

Specifically, letting $h(d_{ijt})$ be the hazard rate for fund-manager i, j at time t and $h_0(d_{ijt})$ be the baseline hazard rate as a function of the duration of the fund-manager's tenure at time t, d_{ijt}, we estimate the following model

$$h(d_{ijt}) = h_0(d_{ijt}) \exp(\beta' x_{ijt}). \tag{14}$$

Our model allows the manager's hazard rate to depend on four factors, x_{ijt}. First, we consider the effect of the duration of manager j's relation with pension fund i at time t, d_{ijt}, measured in quarters. This maps into the baseline hazard, $h_0(d_{ijt})$ which shows how the probability that a manager is fired in the subsequent quarter varies with the duration of the fund-manager contract. An upward-sloping curve indicates that the manager's risk of getting fired increases the longer his contract with a pension fund, while a downward-sloping curve suggests that the manager is less likely to get fired, the longer he has been with a particular pension fund. This part is estimated non-parametrically.

Second, we include $Past\_Risk\_Adj\_Ret$ – constructed by value-weighting the risk-adjusted returns across the various funds managed over the previous two quarters. The hypothesis here is that higher past risk-adjusted returns should reduce the chance of a manager getting fired.

Third, we control for manager size, M_SIZE_{jt}, measured at the beginning of each quarter. We found earlier that this matters for both return performance and fund flows and so it is natural to expect this variable also to be important for managers' prospects of getting fired. Here, the hypothesis is that, after controlling for past return performance, large, established managers are less likely to get fired than smaller managers.

Our final covariate is the centrality measure, NET_{jt}, which is – alternatively – degree centrality, value-weighted prestige centrality, or betweenness centrality. The hypothesis is that the more central a manager is within the network, the less likely she is to get fired.

In summary, our regression model for the hazard rate takes the following form:

$$h(d_{ijt}, Past\_Risk\_Adj\_Ret_{ijt}, M\_SIZE_{jt}, NET_{jt}) =$$
$$h_0(d_{ijt}) \exp(\beta_1 Past\_Risk\_Adj\_Ret_{ijt} + \beta_2 M\_SIZE_{jt} + \beta_3 NET_{jt}) + \varepsilon_{ijt}. \tag{15}$$

The hazard rate increases monotonically in the duration of the fund-manager relation, tripling from around 0.2 - 0.3% per quarter for managers with a tenure of 10 quarters to 0.6% per quarter for managers with a tenure of 70 quarters. While some of this result may be due to a consultant allowing a manager some number of quarters of "burn-in time" to learn about that manager's skills, the firing rate continues to increase as manager duration becomes very large–likely because such managers overuse their strategy as they grow.

Panel A in Table 9 reports estimation results for the model in (15) fitted to the manager data. The hazard rate, i.e., the risk that the manager is fired by a client, is significantly negatively related to past performance. Higher past (risk-adjusted) performance is, thus, associated with a reduced probability that a manager will be fired by the fund. Further, we estimate a large negative, and highly significant, coefficient on manager size, suggesting that large managers face a lower probability of being fired.

Turning to network centrality, all three centrality measures generate coefficients that are negative and significant at the 1% level. Thus, more central managers appear to face a greatly reduced chance of being fired, compared with more peripheral managers.

Panel B of Table 9 shows results from estimating (15) on the consultant data. Past average return performance is no longer a significant predictor of firing events. Consultant size, on the other hand, remains strongly negatively related to the firing probability. Interestingly, consultant centrality is, once again, a negative and significant predictor of future firings across all three centrality measures.

These results establish a strong case that managers' and consultants' network centrality negatively affects their probability of being fired, most likely because of the higher expected future performance associated with higher levels of network centrality.

7 Conclusion

Decentralized investment management is the process by which assets of institutional investors are managed by professional money managers. Not only do institutions such as pension funds employ multiple fund managers, but these fund management houses manage the assets of many pension funds, creating a network of linkages between fund managers and the investment consultants who advise the pension funds. In this paper we use a unique data set on UK pension funds to examine the relation between network centrality measures and fund manager performance, risk taking, fund flows and fund manager tenure – questions that have not previously been addressed in a setting similar to ours.

Our approach analyzes the centrality of the fund's management company by examining the number of connections it has with other management companies through their commonality in managing for the same fund sponsors or through the same fund consultants. Network centrality is found to be positively associated with risk-adjusted return performance and growth in assets under management, after controlling for size and past performance. Moreover, the importance of network centrality is strongest for larger funds, controlling for economies of scale effects. Better connected fund managers also take on higher levels of risk and are less likely to be fired after spells of low performance, demonstrating how network centrality affect fund managers' incentives.

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Appendix A Size and network centrality: Granger causality tests

Table 2 shows that a manager's size and network centrality are positively correlated. Large managers are likely to manage the assets of more clients and so this finding does not come as a surprise. While it can be difficult to formally test if size causes centrality or vice versa, more limited tests of whether one variable precedes the other one are feasible through Granger causality tests.

To implement such Granger causality tests, we first obtain the centrality measure for each manager at each point in time. Similarly, we compute the size of each manager by aggregating investments in all the funds (and asset classes) managed by the manager. We then regress changes in log-size on its own lag and the lag of changes in degree centrality. Because the lagged size and lagged centrality measures are not exogenous, we instrument them using their own lags. To be precise, we use the Holtz-Eakin, Newey, and Rosen (1988) panel estimation method described below to conduct Granger causality tests for the relation between size and network centrality in a panel setting.

Specifically, consider the simple panel model:

$$y_{it} = \lambda_0 + \sum_{l=1}^{m} \lambda_l y_{it-l} + \sum_{l=1}^{m} \delta_l x_{it-l} + \Psi_i + u_{it}. \tag{A1}$$

The model in (A1) can be estimated by pooled OLS that imposes the constraint that the underlying structure is the same for each cross-sectional unit. It allows, however, for an individual specific intercept, Ψ_i. It also allows the variance of the innovation in (A1) to vary with the cross-sectional unit, so as to capture individual heterogeneity in the variability of y.

First-differencing (A1) yields

$$y_{it} - y_{it-1} = \sum_{l=1}^{m} \lambda_l (y_{it-l} - y_{it-l-1}) + \sum_{l=1}^{m} \delta_l (x_{it-l} - x_{it-l-1}) + v_{it}, \tag{A2}$$

where $v_{it} = u_{it} - u_{it-1}$.

Estimation

To estimate the model, define $N \times 1$ vectors of observations on the various units at a given time period, $\mathbf{Y}_t = (Y_{1t}, ..., Y_{Nt})'$ and $\mathbf{X}_t = (X_{1t}, ..., X_{Nt})'$. Let $\mathbf{W}_t = (\mathbf{e}_N,\, \mathbf{Y}_{t-1}, ...,\, \mathbf{Y}_{t-m},\, \mathbf{X}_{t-1}, ...,\, \mathbf{X}_{t-m})$ be the matrix of regressors, where $\mathbf{e}_N$ is an $N \times 1$ vector of ones. Further, let $\mathbf{V}_t = (v_{1t}, ..., v_{mt})'$ be the vector of transformed disturbance terms and let $\mathbf{B} = (a,\ \lambda_1, ..., \lambda_m, \delta_1, ..., \delta_m)'$ be the vector of coefficients. Then we can write (A2) as:

$$\mathbf{Y}_t = \mathbf{W}_t\mathbf{B} + \mathbf{V}_t. \tag{A3}$$

Stacking the observations for each time period, we can simplify this to a system

$$\mathbf{Y} = \mathbf{W}\mathbf{B} + \mathbf{V}. \tag{A4}$$

Finally, defining a set of instrumental variables, $\mathbf{Z}$, we estimate $\mathbf{B}$ from the equation

$$\mathbf{Z}'\mathbf{Y} = \mathbf{Z}'\mathbf{W}\mathbf{B} + \mathbf{Z}'\mathbf{V}. \tag{A5}$$

This specification makes it easy to test whether the coefficients on the $x-$variables are jointly equal to zero by imposing simple linear restrictions and then computing the likelihood ratio test comparing the restricted and unrestricted model.

Our implementation uses one-step GMM estimation and the Arellano-Bond estimator and limits the instruments to a maximum of 16 lags.[36] We separately consider degree, value-weighted prestige and betweenness centrality measures.

Empirical findings

Table A1 presents the outcome of the Granger causality tests described above as applied to our data. Panel A uses centrality as the dependent variable, while lagged size and lagged centrality are used as independent variables. In all instances, lagged size fails to significantly predict centrality, leading to the conclusion that size does not Granger-cause network centrality. As expected, lagged centrality predicts current centrality, consistent with the persistence in the centrality measures revealed in plots such as Figure 4.

Panel B of Table A1 performs the reverse regression, regressing current size on lagged centrality and

[36] We have 81 observations in the time-series and the number of instruments would become unmanageably large otherwise.

past size. Here we find that centrality strongly (and positively) predicts future size, after controlling for past size. Thus, network centrality Granger-causes size, but not the reverse. This result is consistent across all centrality measures. Moreover, the results are robust to the number of lags chosen.[37]

The conclusion from these results is that network centrality adds a novel dimension to our understanding of managers' investment performance, risk-taking behavior, and fund flows. Moreover, network centrality, though positively related to size, is clearly not subsumed by size. In fact, although size and network centrality are positively correlated, size generally has a negative effect on investment performance and fund inflows while conversely network centrality is associated with better risk-adjusted performance and higher inflows.

Appendix B Results controlling for centrality in other asset classes

To the extent that the benefits from network connections arise due to managers' improved ability to receive and process information on the strategies of other managers, we would expect that centrality *within* a specific asset class would matter more than centrality established through other asset classes. For example, a manager's network connections in the UK equity market should be more relevant than the same manager's connections in UK bonds, when it comes to receiving information on strategies that work in UK equity markets.

To assess the impact of asset-class-specific centrality on performance, we modify the procedure in Section 3.1 as follows. For UK equities, we run panel regressions that include network centrality in UK equities as well as centrality in UK bonds. Because the two centrality measures are correlated with each other, we orthogonalize the centrality in UK bonds with respect to the centrality in UK equities at the fund-manager level.[38] Our baseline specification includes centrality in UK equities and the orthogonalized centrality measure for UK bonds. An extended specification includes interactions

[37] We also computed panel Granger causality tests for the relation between quarterly return performance, aggregated across asset classes, and network centrality. The procedure adopted is virtually identical to that described above, with the exception that we control for the effect of manager size, $SIZE\_M$, which we found has an important impact on performance. The results suggest that performance does not Granger-cause centrality. Conversely, our results indicate that network centrality Granger-causes future performance. A more central position in the network thus seems to precede improvements in managers' return performance, while the opposite relation does not hold.

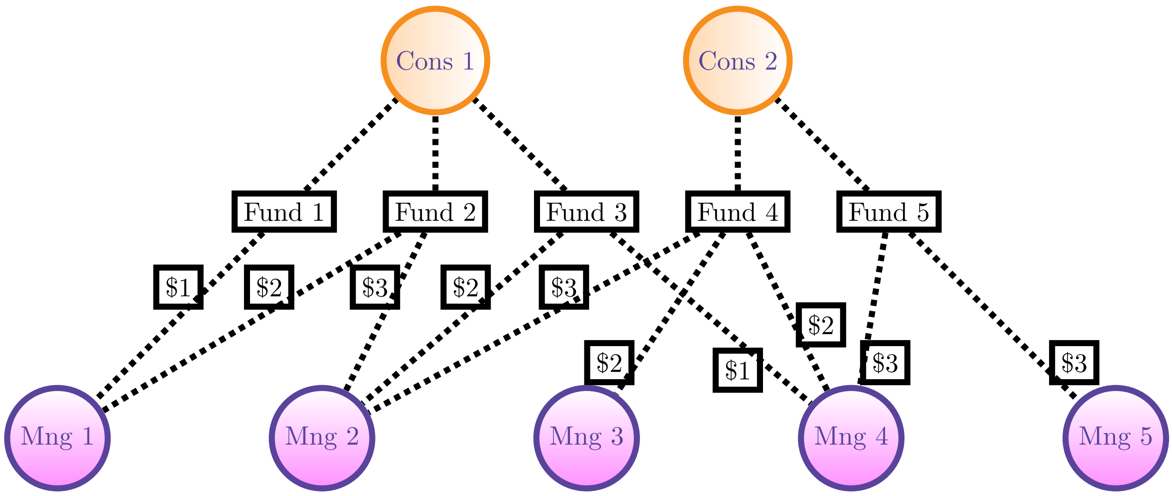
[38] In particular, we regress — at the fund-manager level — UK bond fund centrality on UK equity fund centrality. We then store the residuals, which represent the portion of UK bond fund centrality that is orthogonal with respect to UK equity fund centrality.

of these terms with manager size.

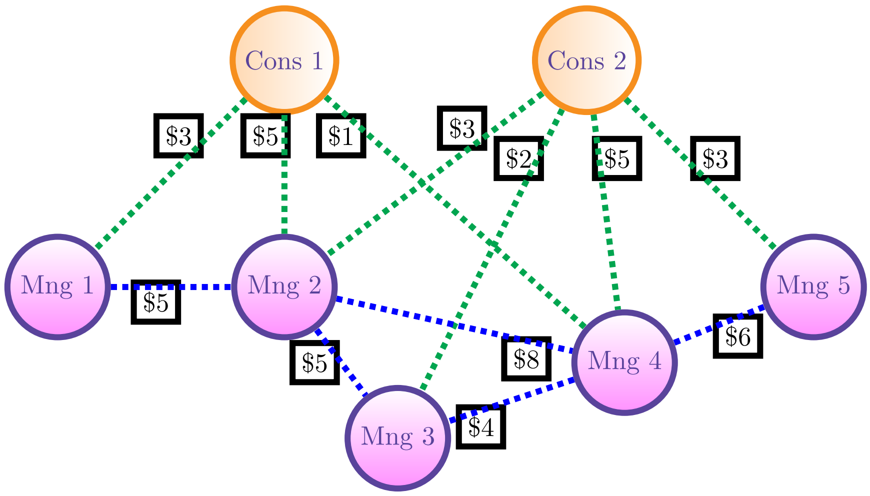
Appendix Table A3 reports results from these regressions. The results show that, after accounting for network connections within UK equities, the performance of UK equity managers is either negatively affected, or insignificantly affected by additional network connections established through the management of UK bond portfolios (and the coefficient on bond centrality is generally much lower, compared to the coefficient on equity centrality). Conversely, the coefficient on network centrality established in UK equities is significant in each model, either alone or when interacted with size. The results remain the same when we interact the centrality measures with manager size: centrality in UK equities generates positive and significant coefficients for this asset class, while centrality in UK bonds generates either negative or insignificant coefficients. These results suggest that asset-class-specific network connections are important in explaining manager performance and also lend support to the hypothesis that the network centrality measure captures fund managers' ability to gather and process information on strategies of importance to risk-adjusted performance within their asset class, and that the centrality measure is not merely acting as a proxy for an omitted variable.

Figure 1. Example of network relations in the UK pension fund industry

Panel A. Extended-form representation



Panel B. Reduced-form representation

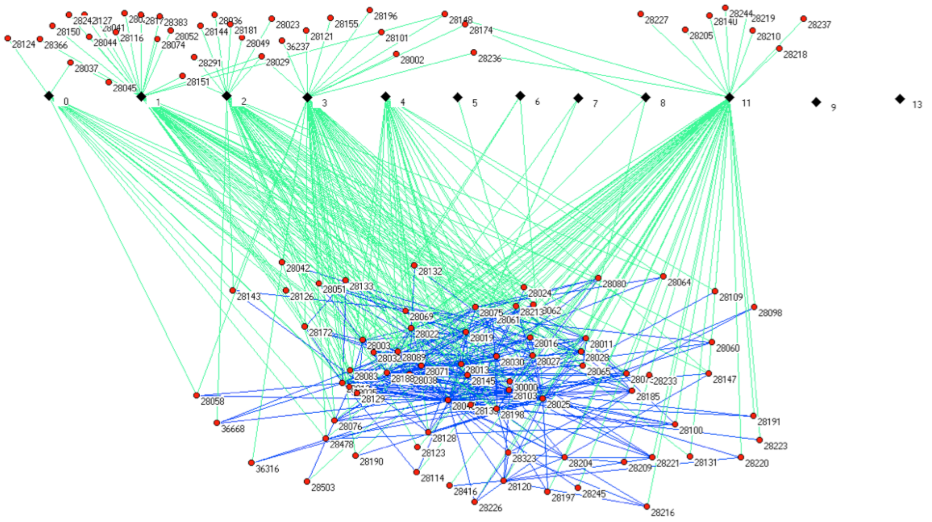


Panel C. Centrality of managers and consultants according to different measures of centrality

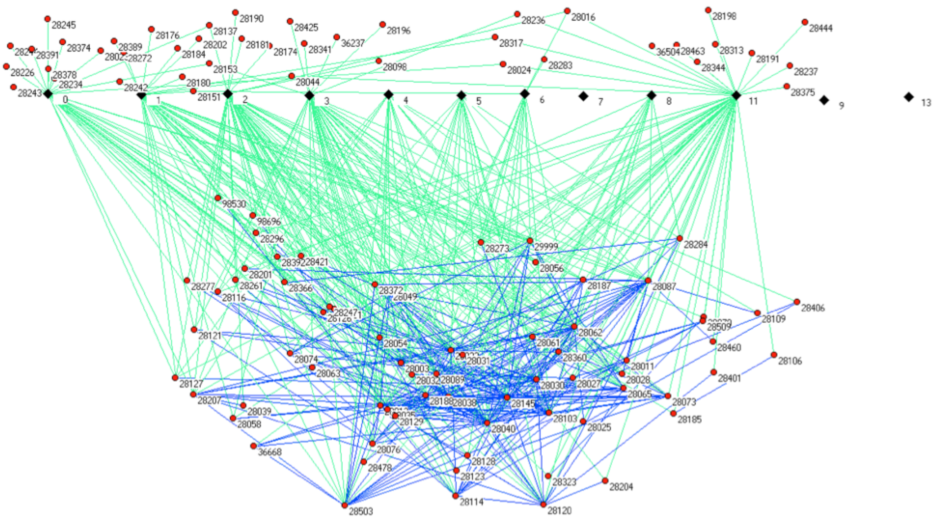
	Cons 1	Cons 2	Mng 1	Mng 2	Mng 3	Mng 4	Mng 5
Degree	0.500	0.667	0.333	0.833	0.500	0.833	0.333
Value-weighted prestige	0.214	0.309	0.190	0.618	0.262	0.571	0.214
Betweenness	0.111	0.178	0.000	0.556	0.000	0.489	0.000

This figure plots an example of the network connections generated by the interplay of five pension funds (Fund 1 through Fund 5), two consultants (Cons 1 and Cons 2) and five managers (Mng 1 through Mng 5). The figure plots the case where: Fund 1 is advised by Cons 1 and employs Mng 1; Fund 2 is advised by Cons 1 and employs Mng 1 and Mng 2; Fund 3 is advised by Cons 1 and employs Mng 2 and Mng 4; Fund 4 is advised by Cons 2 and employs Mng 2, Mng 3, and Mng 4; and Fund 5 is advised by Cons 2 and employs Mng 4 and Mng 5. Panel A reports the extended-form representation of the network, as it displays the full set of connections involving pension funds, managers, and consultants. Panel B reports the reduced-form representation of the network, as it displays only the connections between managers and consultants. In Panel B, the green lines represent consultant-to-manager connections, while blue lines represent manager-to-manager connections – arising from co-managing the same fund. In Panel A, the numbers on the lines that connect the funds to the managers indicate the size of the mandate. In Panel B, they indicate the total assets under management associated with the manager-to-consultant and the manager-to-manager connections – computed across all funds. Panel C reports the value of degree, value-weighted prestige and betweenness centralities for all managers and consultants.

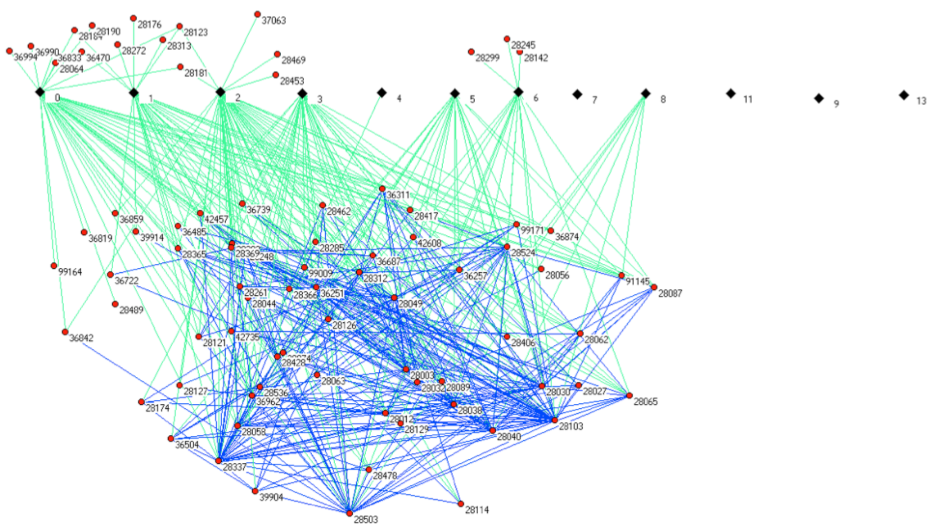
Figure 2. Network connections in UK equities



(A) Year : 1984



(B) Year : 1994

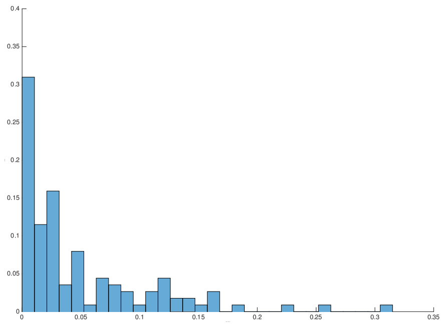


(C) Year : 2004

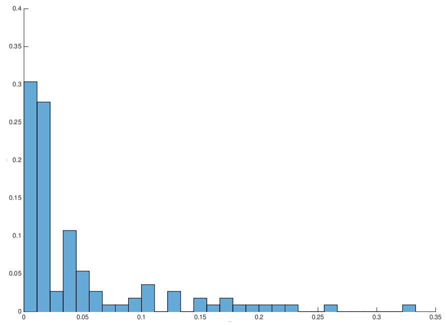
This figure plots the network connections in UK equities at three points in time during our sample, namely 1984, 1994, and 2004. The red circles represent individual managers, while the black diamonds in the horizontal row represent the 12 consultants. Next to each node is shown the code of the manager or consultant. Managers whose nodes are shown above the consultants are only connected through the consultants, while the managers whose nodes fall below the consultants are connected with at least one other manager.

Figure 3. Distribution of centrality measures over time.

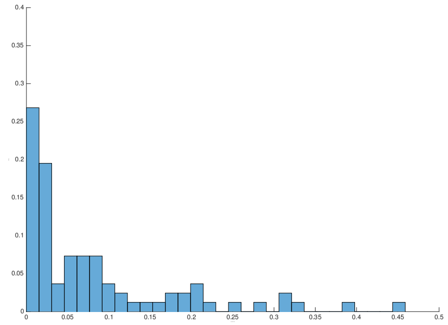
Panel A. Degree centrality



(A) Year: 1984

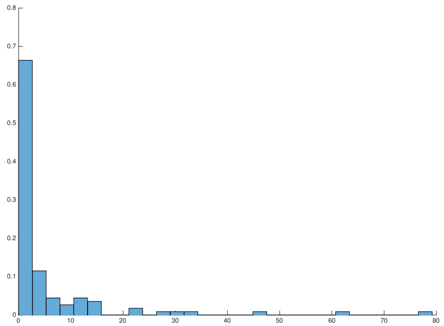


(B) Year: 1994

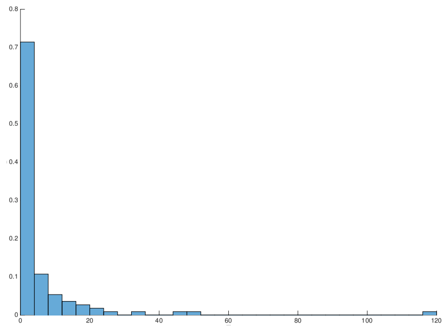


(C) Year: 2004

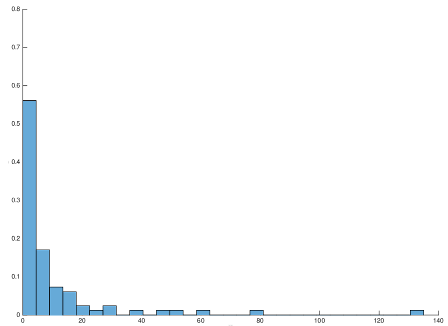
Panel B. Value-weighted prestige centrality



(A) Year: 1984

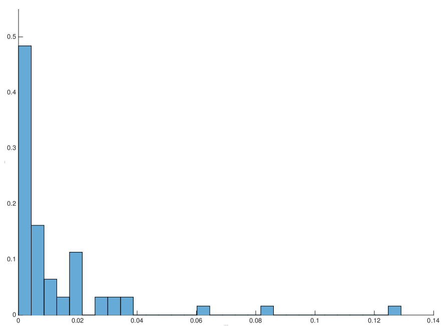


(B) Year: 1994

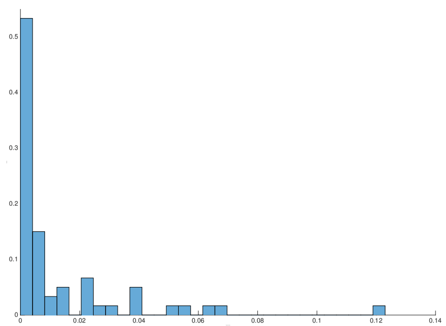


(C) Year: 2004

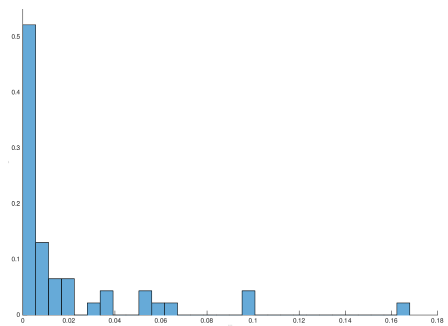
Panel C. Betweenness centrality



(A) Year: 1984



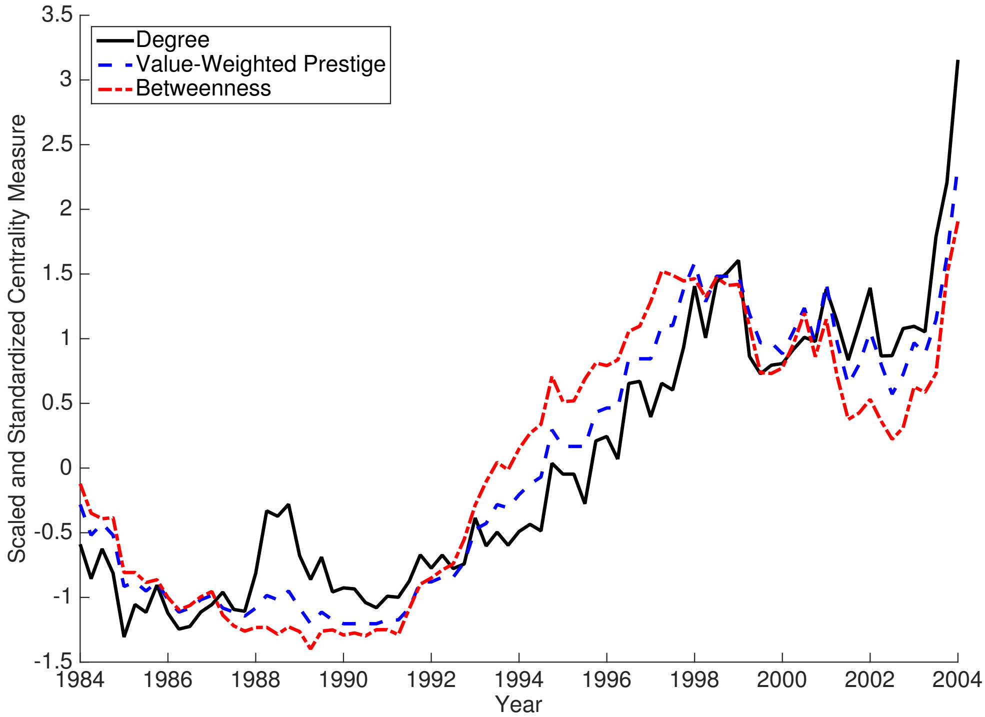
(B) Year: 1994



(C) Year: 2004

This figure plots the cross-sectional distribution of degree centrality in Panel A, value-weighted prestige centrality in Panel B, and betweenness centrality in Panel C – for UK equities. Each panel reports the distribution of the centrality measure under consideration at three points in time: 1984, 1994, and 2004.

Figure 4. Average network centrality over time

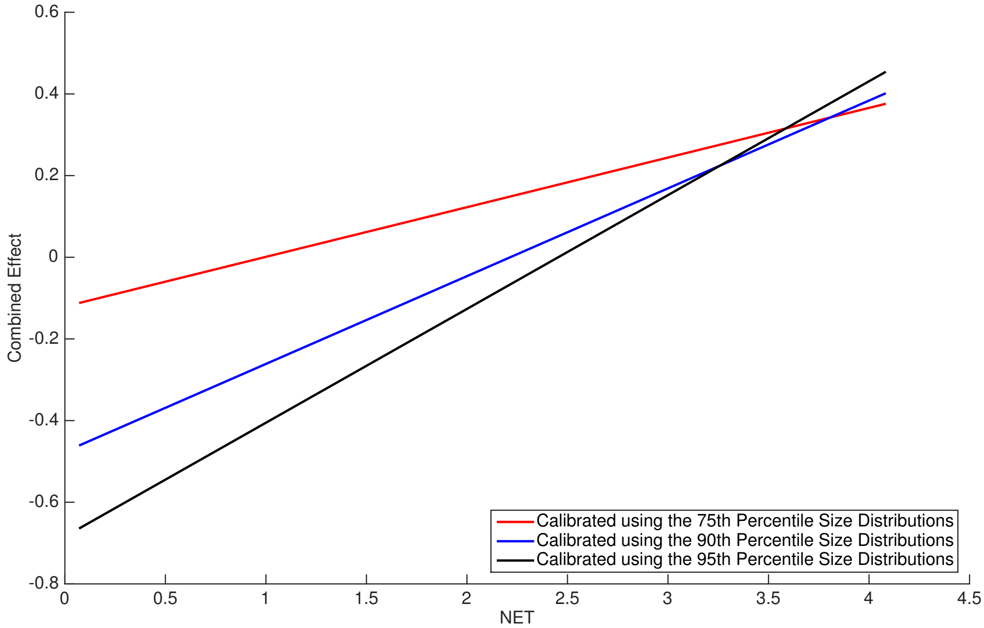


This figure plots the time series of the average degree, value-weighted prestige and betweenness centralities for UK equities. In each panel, each centrality measure NET_t is standardized as follows

$$S\_NET_t = \frac{NET_t - MEAN(NET_t)}{STDEV(NET_t)},$$

where $MEAN(NET_t)$ is the time-series mean of the average centrality measure NET_t and $STDEV(NET_t)$ is its standard deviation.

Figure 5. Combined effect of manager size and network degree centrality on performance



(A) UK equities

This figure plots the combined effect of manager size and degree centrality on risk-adjusted performance for UK equities. To compute these quantities, we focus on particular percentiles of the fund-manager size ($SIZE$) and manager size (M_SIZE): we use, alternatively, the 75th, 90th or 95th percentiles of the size distributions, while we allow the centrality measure NET to vary across its full support. The coefficients used are the ones reported in the second column of Panel A of Table 2. As an example, consider the case of the 75-th percentile of $SIZE$ and M_SIZE and denote them as $SIZE\_75$ and M_SIZE_75. We report the results of the following calculation:

$$\begin{aligned} Combined\_Effect\_of\_Manager\_Size\_and\_Centrality = & -0.292 \times SIZE\_75 \\ & -0.722 \times M\_SIZE\_75 + 0.042 \times NET \\ & +0.365 \times NET \times M\_SIZE\_75, \end{aligned}$$

where we let NET range 0.07 through 4.08.

Table 1. Summary statistics

Panel A. Number of funds, managers and their connections across time

Year	N. of fund-managers	N. of funds	N. of managers	$Net = 1$	$2 \leq Net \leq 5$	$6 \leq Net \leq 10$	$11 \leq Net \leq 20$	$Net \geq 21$
1984	1204	955	113	35	35	15	20	8
1994	1420	1044	112	34	42	14	12	10
2004	1053	630	82	22	23	17	10	10

Panel B. Correlation between centrality and size measures

	Degree	VW_Prestige	Betweenness	$SIZE$	M_SIZE
Degree	1.000				
Value-weighted prestige	0.885	1.000			
Betweenness	0.926	0.915	1.000		
$SIZE$	-0.017	0.006	-0.012	1.000	
M_SIZE	0.637	0.660	0.612	0.092	1.000

This table presents, in Panel A, summary statistics for the number of fund-manager pairings, number of funds, and number of managers in UK equities for the years 1984, 1994 and 2004. For the same years, it also reports the number of managers with one network connection ($Net = 1$), the number of managers with network connections between 2 and 5 ($2 \leq Net \leq 5$), between 6 and 10 ($6 \leq Net \leq 10$), between 11 and 20 ($11 \leq Net \leq 20$), and greater than 20 ($Net \geq 21$). The table reports, in Panel B, the correlation between the centrality measures and the size measures in our dataset. The centrality measures of interest are degree centrality, value-weighted prestige centrality and betweenness centrality – computed for the UK equities asset class. $SIZE$ denotes the assets under management of each fund-manager pairing, while M_SIZE denotes each manager's assets under management across all funds managed. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. The coefficients are obtained by computing cross-sectional correlations in the first step, and taking time-series averages in the second step.

Table 2. Network centrality and performance

	Panel A. Degree				Panel B. Value-weighted prestige				Panel C. Betweenness			
$SIZE$	-0.284 (0.14)	-0.292 (0.13)	-0.299 (0.12)	-0.307 (0.11)	-0.287 (0.13)	-0.316 (0.10)	-0.303 (0.12)	-0.332 (0.08)	-0.285 (0.14)	-0.283 (0.13)	-0.301 (0.12)	-0.299 (0.12)
M_SIZE	-0.631 (0.00)	-0.722 (0.00)	-0.640 (0.00)	-0.733 (0.00)	-0.659 (0.00)	-0.362 (0.02)	-0.669 (0.00)	-0.371 (0.02)	-0.608 (0.00)	-0.631 (0.00)	-0.617 (0.00)	-0.640 (0.00)
NET	0.197 (0.04)	0.042 (0.68)	0.203 (0.03)	0.046 (0.66)	0.304 (0.00)	-0.948 (0.00)	0.314 (0.00)	-0.944 (0.00)	0.230 (0.00)	0.068 (0.31)	0.237 (0.00)	0.072 (0.28)
$NET \times M\_SIZE$		0.365 (0.00)		0.372 (0.00)		1.066 (0.00)		1.071 (0.00)		0.325 (0.00)		0.332 (0.00)
Consultant fixed-effects	✗	✗	✓	✓	✗	✗	✓	✓	✗	✗	✓	✓
Fund-manager fixed-effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

This table reports results for panel regressions of fund-managers' risk-adjusted performance in UK equities on managers' degree centrality (Panel A), value-weighted prestige centrality (Panel B), and betweenness centrality (Panel C). The risk-adjusted return of manager j in fund i at time t is computed as $\widehat{r}^{adj}_{ijt} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using return observations on manager j's account in fund i. We adopt a four-factor model:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK stock market index, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We drop from the sample the fund-manager pairings that have less than 12 observations. The panel regressions use as control variables the assets under management in UK equities of each fund-manager pairing ($SIZE$), as well as each manager's assets under management in UK equities across all funds managed (M_SIZE). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. For each centrality measure we adopt four specifications. The first two columns do not include consultant fixed effects, while the remaining two columns do. Furthermore, the first and third columns include only the centrality measure, while the second and fourth columns include the centrality measure and its interaction with manager size. All specifications use fund-manager and time fixed effects. P-values (reported in parentheses) are computed using standard errors that are clustered at the fund-manager level.

Table 3. Return correlations for connected and non-connected managers

Correlation-type	Connected managers	Non-connected managers	Diff.	P-val.	Obs.
Returns	0.954	0.949	0.005	0.649	139
Factor-explained returns	0.978	0.978	0.000	0.968	139
Residuals	0.170	0.096	0.074	0.000	139

This table compares – for UK equities – return correlations between managers that are connected to each other and managers that are not connected to each other. Performance is measured as returns (first row), factor-explained returns (second row), and return residuals (third row). The results for returns are computed as follows. We first compute returns at the manager level by value-weighting the returns in each fund managed by a given manager. We then compute return correlations between each manager and every other manager contained in the dataset, making sure to use only manager pairings that overlap for at least 12 quarters. Third, for each manager, we average the return correlations associated with connected and non-connected managers. Fourth, for connections and non-connections, we compute the median of the average correlations across all the managers in the dataset. Finally, we compute tests of differences in medians across the two sets of correlations based on two-sided permutation tests that use 1,000 iterations. The procedure is repeated for other measures of performance, i.e., factor-explained returns and return residuals.

Table 4. Network effect of the merger between two consultants

	Degree	**Value-weighted prestige**	**Betweenness**
Treatment×NET	0.153	0.087	0.074
	(0.02)	(0.08)	(0.09)
NET	0.193	0.318	0.221
	(0.04)	(0.00)	(0.00)
$SIZE$	-0.281	-0.285	-0.284
	(0.14)	(0.13)	(0.14)
M_SIZE	-0.646	-0.679	-0.617
	(0.00)	(0.00)	(0.00)

This table reports the effect of a shock to network centrality – due to the merger of two consultants – on risk-adjusted performance in UK equities. In the first step we compute the risk-adjusted return of manager j in fund i at time t as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using the full set of observations available for manager j in fund i. We adopt a four-factor model:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK stock market index, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We drop from the sample the fund-manager pairings that have less than 12 observations. In the second step, we estimate

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} \times M\_Dummy_{jt} + \varepsilon_{ijt},$$

where the merger treatment dummy M_Dummy_{jt} is switched on for 3 years for all managers affected by the merger between the two consultants Mercer and Sedgwick – that occurred on October 1, 1998. The panel regressions use as control variables the assets under management of each fund-manager pairing (denoted by $SIZE$), as well as each manager's assets under management in UK equities across all funds managed (denoted by M_SIZE). The centrality measures of interest are degree centrality, value-weighted prestige centrality and betweenness centrality. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measure NET is converted to relative centrality by dividing each entry by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. All the specifications use fund-manager and time fixed effects. The p-values are reported in parentheses and are computed using standard errors that are clustered at the fund-manager level.

Table 5. Consultant alphas in UK equities

	Annualized alphas
Consultant 1	0.091 (0.51)
Consultant 2	0.071 (0.58)
Consultant 3	0.006 (0.96)
Consultant 4	-0.645 (0.06)
Consultant 5	0.075 (0.69)
Consultant 6	-0.070 (0.74)
Consultant 7	-0.019 (0.97)
Consultant 8	-0.035 (0.91)
Consultant 11	-0.202 (0.11)

This table reports the annualized consultant alphas in UK equities. In particular, it reports the α_c coefficients associated with the following regression in UK equities:

$$r_{ict} = k + \alpha_c + \beta_{1ic}\ r_{mkt,t} + \beta_{2ic}\ SMB_t + \beta_{3ic}\ HML_t + \beta_{4ic}\ MOM_t + \epsilon_{ict},$$

where i refers to the fund, c refers to the consultant and t refers to the time period. Notice that we allow for consultant-fund differences by allowing the betas to differ across consultant-fund pairings. Standard errors are clustered at the fund-consultant level.

Table 6. Style and centrality

	Panel A. Degree				Panel B. Value-weighted prestige				Panel C. Betweenness			
	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}
$SIZE$	0.004	0.010	0.003	0.001	0.004	0.007	0.000	0.002	0.005	0.012	0.001	0.001
	(0.24)	(0.14)	(0.61)	(0.81)	(0.23)	(0.30)	(0.96)	(0.70)	(0.10)	(0.08)	(0.83)	(0.78)
M_SIZE	-0.005	-0.012	-0.023	0.006	-0.005	0.009	-0.004	0.001	-0.013	-0.019	-0.008	0.002
	(0.40)	(0.29)	(0.03)	(0.51)	(0.26)	(0.31)	(0.62)	(0.89)	(0.00)	(0.03)	(0.31)	(0.71)
NET	0.004	0.017	0.029	-0.013	0.005	-0.009	0.010	-0.009	0.015	0.031	0.015	-0.011
	(0.49)	(0.11)	(0.00)	(0.10)	(0.27)	(0.31)	(0.20)	(0.12)	(0.00)	(0.00)	(0.04)	(0.06)

This table reports results on the relation between fund-manager style and centrality in UK equities. The results are computed as follows. In the first step, we estimate – for manager j in fund i at time t – time-varying coefficients for the market, SMB, HML, and MOM factors using a 12 quarter rolling window. We then compute quarterly variations in the exposure of each fund-manager pairing to each risk-factor as follows:

$$\Delta\beta_{Factor,ijt} = (\beta_{Factor,ijt} - \beta_{Factor,ij,t-1}) \times 12.$$

In the last step, we estimate – for each risk-factor – the following panel regression:

$$\Delta\beta_{Factor,ijt} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \varepsilon_{ijt},$$

where $SIZE$ denotes the assets under management of each fund-manager pairing, M_SIZE denotes the manager's assets under management in UK equities across all funds managed, and NET denotes degree centrality in Panel A, value-weighted prestige centrality in Panel B, and betweenness centrality in Panel C. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. All specifications use fund-manager and time fixed effects. P-values (reported in parentheses) are computed using standard errors that are clustered at the fund-manager level.

Table 7. Fund flows and manager centrality

Panel A. Flows from newly assigned mandates

	Degree	**Value-weighted prestige**	**Betweenness**
NET	16.182	10.241	10.146
	(0.00)	(0.00)	(0.00)
Lag_Flow	0.080	0.079	0.081
	(0.09)	(0.10)	(0.09)
M_SIZE	-7.711	-1.635	-2.273
	(0.00)	(0.55)	(0.29)
Past_Risk_Adj_Ret	0.597	0.525	0.529
	(0.24)	(0.28)	(0.27)

Panel B. Flows from existing mandates

	Degree	**Value-weighted prestige**	**Betweenness**
NET	9.879	18.493	0.088
	(0.40)	(0.32)	(0.99)
Lag_Flow	0.107	0.102	0.108
	(0.01)	(0.01)	(0.01)
M_SIZE	-22.783	-23.939	-16.631
	(0.05)	(0.03)	(0.06)
Past_Risk_Adj_Ret	1.841	1.743	1.826
	(0.10)	(0.12)	(0.10)

This table reports panel regression results for the effect of manager centrality, size and past performance on fund inflows and outflows from existing mandates and newly assigned mandates. For newly assigned mandates (Panel A), the fund-flow variable for manager j over quarter t is the value of the newly assigned mandates. For existing mandates (Panel B), the fund-flow variable for manager i over quarter t is defined as:

$$Flow_{jt+1} = \left(\frac{M\_SIZE_{jt+1} - M\_SIZE_{jt}}{M\_SIZE_{jt}} - R_{jt:t+1} \right) M\_SIZE_{jt},$$

where M_SIZE_{jt} and M_SIZE_{jt+1} are the starting market values (of existing mandates) of manager j's asset holdings at quarter t and $t+1$ and $R_{jt:t+1}$ is the return generated over quarter t. The analysis is performed for UK equities and the centrality measures of interest are degree centrality, value-weighted prestige centrality, and betweenness centrality – computed in UK equities. The size variable M_SIZE denotes the total assets under management (across all funds managed) of each manager at each point in time. For each manager, *Past_Risk_Adj_Ret* is constructed by value-weighting the risk-adjusted returns in a given asset class across the funds managed over the previous year. Risk-adjusted returns are computed using the model described in the caption of Table 2. We convert the size variable to relative size by dividing it by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series – with the exception of lagged-flows – has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. All results are computed using manager and time fixed effects. P-values (reported in parentheses) are computed using standard errors that are clustered at the manager level.

Table 8. Centrality and fund-manager risk

	Degree	Value-weighted prestige	Betweenness
NET	0.258	0.487	0.072
	(0.00)	(0.00)	(0.29)
$SIZE$	-0.375	-0.364	-0.403
	(0.00)	(0.00)	(0.00)
M_SIZE	-0.567	-0.702	-0.390
	(0.00)	(0.00)	(0.00)

This table reports results for cross-sectional regressions of fund-managers' risk in UK equities on manager degree centrality (first column), value-weighted prestige centrality (second column) and betweenness centrality (third column). The results are computed by regressing the average risk of each fund-manager pairing on average fund-manager size, manager centrality, and manager size. We take $|\hat{\epsilon}_{ijt}|$ (described further below) as the measure of risk for manager j in fund i at time t. We then subtract the cross-sectional average, computed using all the fund-manager pairings available at each point in time. Third, we compute the time-series average of the de-meaned absolute residuals at the fund-manager level and use it as our average risk variable. We repeat a similar procedure for managers' centrality, managers' size, and fund-managers' size. In particular, the size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Finally, we regress, at the fund-manager level, the average absolute residual on average centrality (NET), fund-manager size (denoted by $SIZE$), manager size (M_SIZE). Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. P-values are reported in parentheses. To compute $|\hat{\epsilon}_{ijt}|$, we use a four-factor model:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK stock market index, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We drop from the sample the fund-manager pairings that have less than 12 observations.

Table 9. Survival analysis for managers and consultants

Panel A. Analysis at the manager level

	Degree	Value-weighted prestige	Betweenness
Past_Risk_Adj_Ret	-0.083	-0.089	-0.089
	(0.00)	(0.00)	(0.00)
SIZE	-0.192	-0.199	-0.208
	(0.00)	(0.00)	(0.00)
NET	-0.332	-0.415	-0.378
	(0.00)	(0.00)	(0.00)

Panel B. Analysis at the consultant level

	Degree	Value-weighted prestige	Betweenness
Past_Risk_Adj_Ret	-0.000	-0.001	-0.000
	(0.99)	(0.96)	(0.99)
SIZE	-0.299	-0.282	-0.315
	(0.00)	(0.00)	(0.00)
NET	-0.099	-0.035	-0.110
	(0.00)	(0.13)	(0.00)

This table reports in Panel A (Panel B) the coefficients from a Cox proportional hazard rate model relating the probability of managers' (consultants') contracts being terminated in UK equities to their past performance, their size, as well as their network centrality. In Panel A, *SIZE* denotes the assets under management of each fund-manager pairing. In Panel B, *SIZE* denotes the assets under management of each fund-consultant pairing. Past performance (*Past_Risk_Adj_Ret*) is computed as the average abnormal returns in UK equities over the previous two quarters for each fund-manager pairing in Panel A and for each fund-consultant pairing in Panel B. In Panel A the centrality measure of interest are managers' degree centrality, value-weighted prestige centrality and betweenness centrality. In Panel B the centrality measure of interest are consultants' degree centrality, value-weighted prestige centrality and betweenness centrality. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. *P*-values are reported in parentheses.

Table A1. Granger causality tests of size versus network centrality

Panel A. Dependent variable: centrality measure

	Degree	**Value-weighted prestige**	**Betweenness**
M_SIZE	-0.001 (0.39)	-0.438 (0.01)	-0.000 (0.86)
NET	0.885 (0.00)	0.965 (0.00)	0.900 (0.00)

Panel B. Dependent variable: size

	Degree	**Value-weighted prestige**	**Betweenness**
M_SIZE	0.619 (0.00)	0.650 (0.00)	0.650 (0.00)
NET	2.321 (0.00)	0.002 (0.10)	3.452 (0.00)

This table reports the results of panel Granger causality tests for manager size and centrality. Manager centrality is computed – alternatively – as degree centrality, value-weighted prestige centrality and betweenness centrality and all measures of centrality are computed across all asset classes managed. Manager size is computed as the log of the total assets under management across funds and asset classes. The dependent variable is manager centrality in Panel A and manager size in Panel B. The parameters are estimated using a one-step GMM that uses up to 16 lags of the dependent variable as instruments. Details of the procedure are reported in Appendix B of the paper. P-values are reported in parentheses and are computed using robust standard errors.

Table A2. Network centrality and performance

Manager-to-manager and consultant-to-manager degree centrality

$SIZE$	-0.287 (0.14)	-0.302 (0.12)
M_SIZE	-0.668 (0.00)	-0.677 (0.00)
DEG_C	0.130 (0.08)	0.129 (0.08)
DEG_M	0.119 (0.17)	0.126 (0.15)
Consultant fixed-effects	✗	✓
Fund-manager fixed-effects	✓	✓
Time fixed-effects	✓	✓

This table reports results for panel regressions of fund-managers' risk-adjusted performance in UK equities on managers' degree centrality computed using manager-manager connections (DEG_M) and consultant-manager connections (DEG_C). The risk-adjusted return of manager j in fund i at time t is computed as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using return observations on manager j's account in fund i. We adopt a four-factor model:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK stock market index, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We drop from the sample the fund-manager pairings that have less than 12 observations. The panel regressions use as control variables the assets under management in UK equities of each fund-manager pairing ($SIZE$), as well as each manager's assets under management in UK equities across all funds managed (M_SIZE). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. For each centrality measure we adopt four specifications. The first two columns do not include consultant fixed effects, while the remaining two columns do. Furthermore, the first and third columns include only the centrality measure, while the second and fourth columns include the centrality measure and its interaction with manager size. All specifications use fund-manager and time fixed effects. P-values (reported in parentheses) are computed using standard errors that are clustered at the fund-manager level.

Table A3. Effect of centrality on performance in UK equities, controlling for centrality in UK bonds

	Specification 1	Specification 2
$SIZE$	-0.285	-0.291
	(0.14)	(0.13)
M_SIZE	-0.619	-0.709
	(0.00)	(0.00)
NET_BONDS	-0.070	-0.084
	(0.00)	(0.00)
$NET\_EQUITIES$	0.179	0.022
	(0.06)	(0.83)
$NET\_BONDS \times M\_SIZE$		-0.053
		(0.00)
$NET\_EQUITIES \times M\_SIZE$		0.363
		(0.00)

This table reports results for panel regressions of fund-managers' risk-adjusted performance in UK equities on managers' centrality. The risk-adjusted return of manager j in fund i at time t is computed as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using return observations on manager j's account in fund i. We adopt a four-factor model for UK equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK stock market index, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We drop from the sample the fund-manager pairings that have less than 12 observations. The centrality measure of interest is degree centrality ($NET\_EQUITIES$), computed in UK equities. The degree centrality measure computed for UK bonds (NET_BONDS) is used as control and is orthogonalized with respect to $NET\_EQUITIES$ at the fund-manager level. We use as additional control variables the assets under management in UK equities of each fund-manager pairing (denoted by $SIZE$), as well as each manager's assets under management in UK equities across all funds managed (M_SIZE). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. We adopt two specifications. In the first we include only the centrality measures. In the second we include the centrality measures and their interaction with manager size. All the specifications use fund-manager and time fixed effects. P-values (reported in parentheses) are computed using standard errors that are clustered at the fund-manager level.